STORMSIGHT

Deep Learning based Cyclone Intensity Estimation using INSAT-3D IR Imagery

Guided By

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Agenda

Abstract

The tropical cyclones in India is a common natural disaster happening every year. As per the statistics, about three cyclones hit India's east coast in the Bay of Bengal, which damaged human lives, crops and property. It is essential to predict the cyclones in advance to prevent and reduce huge damage. The techniques used are based on numerical models that require vast expertise and higher skill sets to achieve better prediction accuracy. Hence, Our project introduces use of deep learning techniques to estimate cyclone intensity, utilizing INSAT-3D infrared (IR) imagery. We develop a Convolutional Neural Network (CNN) model, training it on a labeled dataset of cyclones. The goal is to significantly enhance the accuracy and speed of real-time cyclone intensity predictions, ultimately contributing to more effective disaster preparedness and response.

Introduction

In this work, we present a novel application of deep learning techniques utilizing INSAT-3D IR imagery for estimating cyclone intensity. Our primary objective is to develop a robust Convolutional Neural Network (CNN) model capable of extracting crucial features from IR images and subsequently training it on a labeled dataset of cyclones. The ultimate goal is to significantly improve the accuracy and speed of real-time cyclone intensity predictions, thereby contributing to more effective disaster preparedness and response efforts.

Literature Review

TITLE :

Tropical Cyclone Intensity Estimation Using Multidimensional Convolutional Neural Network From Multichannel Satellite Imagery

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
1	10.1109/LGRS.2021.3134007	Deep learning methods have been applied to TC intensity estimation, but most of them fail to make full use of multichannel satellite imageries	The goal of the research is to improve the accuracy of tropical cyclone (TC) intensity estimation using deep learning methods by incorporating multichannel satellite imageries by considering the three-dimensional (3-D) structure of TC.	The researchers designed a deep learning model called 3DAttentionTCNet, for tropical cyclone (TC) intensity estimation. They removed the pooling layers and dropout layer to prevent the loss of important intensity features and negative deviations	This model outperformed existing methods for tropical cyclone (TC) intensity estimation. with an RMSE of 9.48 kts	Suggested future research could explore further enhancements in modeling, potentially incorporating additional data sources or advanced techniques.	Our research contributes to bridging the gap by leveraging deep learning for TC intensity estimation. By accounting for the unpredictable nature of TC intensities and **incorporating environmental factors into our model.**

Literature Review

TITLE :

A Novel Deep Learning Based Model for Tropical Intensity Estimation and Post-Disaster Management of Hurricanes

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
2	https://doi.org/10.3390/app11094129	The author identifies the prediction of severe weather events, particularly hurricanes, as a challenging task in climate research, leading to significant hazards to human life, habitats, and economic losses.	The researchers aim to improve the prediction accuracy of hurricane severity and minimize the significant losses caused by hurricanes in terms of human life, habitats, and economic impact.	The researchers employ a deep convolutional neural network (CNN) model for predicting the intensity of hurricanes using infrared satellite imagery data and wind speed data from the HURDAT2 database. They also incorporate batch normalization and dropout layers in the CNN model to improve prediction accuracy.	It achieves a lower Root mean squared error (RMSE) value of 7.6 knots and a Mean squared error (MSE) value of 6.68 knots by adding batch normalization and dropout layers to the CNN model	The authors suggest that future research can focus on improving the accuracy of hurricane intensity estimation by considering additional factors such as the location of the hurricane, intensity, forward speed, and storm surge.	Our research strives to bridge the gap by focusing on considering features like forward speed, storm surge and location of hurricane intensity enhance the prediction model's efficiency.

Literature Review

TITLE :

Deepti: Deep-Learning-Based Tropical Cyclone Intensity Estimation System

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors) ence	Recommendations for future research	how can your research help bridge the gap
3	10.1109/JSTARS.2020.3011907	• The authors identified the need for an accurate diagnostic model for tropical cyclone intensity estimation using satellite data to mitigate the wide range of associated hazards. • Existing techniques and approaches for diagnosing tropical cyclone wind speed using satellite data had varying levels of success.	To develop a deep-learning-based objective, diagnostic estimate of tropical cyclone intensity from infrared satellite imagery with a low root mean squared error of 13.24 knots.	The research paper utilizes a deep learning approach for tropical cyclone intensity estimation from infrared satellite imagery The model is trained using the stochastic gradient descent (SGD) algorithm, which updates the parameters during training with respect to a minibatch to reduce variance and achieve stable convergence	The model inputs training samples at 5-kn speed intervals and outputs a maximum wind speed at 1-kn resolution and a root mean squared error of 13.24 kn.	Various future work could be considered including use of **passive microwave data** to estimate wind speed for tropical cyclones at lower intensity. Detailed analysis of a particular storm to understand model performance with storm structural changes **during rapid intensification**	Our research can contribute to bridging the gap by exploring the utilization of passive microwave data for **estimating wind speed in lower-intensity** tropical cyclones, expanding the applicability of our approach.

Literature Review

TITLE :

Using Deep Learning to Estimate Tropical Cyclone Intensity from Satellite Passive Microwave Imagery

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
4	https://doi.org/10.1175/MWR-D-18-0391.1	The author identifies the problem of estimating tropical cyclone (TC) intensity from satellite images and the challenges associated with it, such as uncertain TC center-fixing and the need for contextual information in the output.	The research aims to assess the contribution of different data sources, such as the 37-and 85-92-GHz bands, in estimating TC intensity and identify the limitations of the model, particularly in the category 5 intensity range	The research utilizes a deep learning CNN model called "DeepMicroNet" to estimate tropical cyclone (TC) intensity from satellite images . The model operates on satellite images in the 37-and 85-92-GHz bands, with the 85-92-GHz band being the more influential data source .	The research highlights the unique properties of DeepMicroNet, such as its probabilistic output and **ability to operate from partial scans**, which come more easily with deep learning than with existing approaches .	The research acknowledges the limitations of the **current dataset** and suggests that further development and exploration can be pursued with more advanced DL methods and expanded training datasets	Our research offers a path towards bridging the existing gap in cyclone prediction by embracing the potential of **incorporating a wider array of data sources**, including satellite imagery and ancillary data.

Literature Review

TITLE :

Interpretable Tropical Cyclone Intensity Estimation Using Dvorak-Inspired Features and Deep Learning

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
5	https://doi.org/10.1016/j.engappai.2021.104233	The problem identified by the authors is the difficulty in directly measuring the intensity of tropical cyclones **when they are located over the open ocean**, as direct intensity measurements are difficult to obtain.	To develop an interpretable system for tropical cyclone intensity estimation using **spatial** and temporal relationships in satellite images.	Utilization of spatial and temporal relationships in satellite images to estimate tropical cyclone intensity. The system employs a random walk with a restart (RWR) model to discover hidden correlations between target and historical cyclone images and uses machine learning models to determine temporal relationships among images.	The system achieves a 15.77-knot root-mean-square error (RMSE) in intensity estimation for tropical cyclones in the West Pacific Basin area, offering interpretable intensity predictions.	They highlight the potential of **combining different meteorological variables,** such as wind speed and direction, to further improve prediction results.	Our research bridges this gap by demonstrating the potential of integrating various meteorological variables, **including wind speed and direction**, to enhance prediction outcomes.

Literature Review

TITLE :

Tropical Cyclone Intensity Estimation Using Multi-Dimensional Convolutional Neural Networks from Geostationary Satellite Data

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
6	https://doi.org/10.3390/rs12010108	The problem identified by the authors is the lack of a standardized method for estimating tropical cyclone (TC) intensity, which leads to bias in the existing manual algorithm using satellite-based cloud images	The researchers aim to overcome the limitations of the existing manual algorithm by leveraging deep learning techniques to analyze image patterns and mimic human cloud pattern recognition.	They specifically explore the use of two-dimensional CNNs (2D-CNN) and three-dimensional CNNs (3D-CNN) to analyze the relationship between multi-spectral geostationary satellite images and TC intensity.	They found that both 2D-CNN and 3D-CNN can effectively analyze the relationship between multi-spectral satellite images and TC intensity. The optimized model produced a root mean squared error (RMSE) of 8.32 kts, resulting in better performance than the existing model using a single-channel image.	The use of CNN-based models in TC intensity estimation can be expanded to include other variables and parameters to better understand the causal relationships among them	Our research bridges this gap by demonstrating the potential of integrating various meteorological variables, **including wind speed and direction**, to enhance prediction outcomes.

Literature Review

TITLE :

An effective tropical cyclone intensity estimation model using Convolutional Neural Networks

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
7	https://doi.org/10.54302/mausam.v72i2.616	The problem identified by the authors is the need for accurate prediction of tropical cyclone intensity in order to prevent and reduce damage caused by these natural disasters.	To estimate tropical cyclone intensity in the North Indian Ocean basin using a CNN-based approach.	The research also acknowledges the challenges in accurately identifying tropical cyclone intensity and the need to consider basic parameters like Sea Surface Temperature (SST), humidity, and wind speed in automated models	They conducted experiments and compared the performance of their model with state-of-the-art techniques, demonstrating that their approach yielded better results in terms of prediction accuracy and reduced computation time .	The authors emphasize the efficiency of models like LeNet, ResNet, AlexNet, and Yolo for image recognition and object detection, making them highly suitable for cyclone intensity prediction	Our research introduces a promising avenue for improving cyclone intensity prediction by incorporating INSAT-3D IR imagery and advanced deep learning techniques. By considering future enhancements like incorporating sea pressure data, our work can help bridge the gap in cyclone prediction accuracy, thereby enhancing early warning systems and disaster preparedness.

Literature Review

TITLE :

Deep learning in extracting tropical cyclone intensity and wind radius information from satellite infrared images

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
8	https://doi.org/10.1016/j.aosl.2023.100373	The problem addressed in this review is the need for more effective and accurate methods to extract tropical cyclone (TC) information, including TC intensity and wind radius, from satellite infrared images to enhance real-time monitoring and improve safety measures for TC-related threats.	Pre-training and fine-tuning approaches using transfer learning can address the challenges posed by different sensors on Earth-observing satellites, improving the performance and generalization ability of deep-learning models	Evaluate deep learning's advantages in TC information extraction, focusing on deep learning frameworks	this paper highlights the practical implications of using deep-learning frameworks for TC information extraction, including improved accuracy, robustness with limited data, and the potential for enhancing real-time monitoring and safety measures.	Address issues like data scarcity, sensor differences, generalization, and interpretability in future research	Our research aims to bridge critical gaps in tropical cyclone prediction by addressing key challenges. We propose data augmentation and transfer learning techniques to build robust deep-learning models despite sparse data.

Literature Review

TITLE :

Probabilistic forecasting of tropical cyclones intensity using machine learning model

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
9	https://doi.org/10.1088/1748-9326/acc8eb	The problem addressed in this study is the lack of reliable probabilistic forecasting for tropical cyclone intensity using machine learning, which aims to provide a solution for characterizing and representing uncertainty in TC forecasts.	The proposed hybrid modeling of NGBoost and LightGBM achieves comparable performance to current state-of-the-art statistic-dynamical and dynamical models on 24-hour deterministic forecasts.	The study utilizes a machine learning approach for probabilistic forecasting of tropical cyclone (TC) intensity, specifically employing a hybrid modeling technique combining NGBoost and LightGBM . It visualizes probability density prediction curves for hurricanes ETA and Laura to demonstrate the effectiveness of the proposed model in probabilistic forecasting	The proposed model offers the advantage of obtaining uncertainty forecasts directly without the need for computationally intensive methods, and it outperforms data-driven models operated by the NHC in most years tested .	Future research could explore the use of deep learning sequential models to capture time series characteristics and consider incorporating advanced TC dynamical models for hybrid modeling.	our application takes this research a step further by providing a user-friendly, real-time solution for estimating TC intensity, making this critical information accessible to a wider audience.

Literature Review

TITLE:

A Lightweight Multitask Learning Model With Adaptive Loss Balance for Tropical Cyclone Intensity and Size Estimation

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
10	10.1109/JSTARS.2022.3225154	Accurate tropical cyclone (TC) intensity and size estimation are key in disaster management and prevention. While great breakthroughs have been made in TC intensity estimation research, there is currently a lack of research on TC size reflecting TC influence radius.	1) To develop a learning model (TC-MTLNet) with adaptive loss balance to simul-taneously estimate TC intensity 2)To develop a model which helps in Estimation of size of Tropical Cyclone .	1) The model based on four 2-D convolutions, four 3-D convolutions and three fully connected layers takes up less computational and storage space. 2) lightweight multitask learning model (TC-MTLNet) with parallel dual attention to estimate TC intensity and size intensity	TC-MTLNet achieves an intensity estimation RMSE of 8.40 kts, lower by 33.5% compared to ADT and 11.4% compared to 3DAttentionTCNet. It also outperforms in size estimation compared to MTCSWA.	**Model performance is lower when TC size increases,** which may be because more complex meteorological factors are involved in the outer wind radius, which is a great challenge for our model and is worth studying in the future.	In Our Project we take **EYE & EYE-WALL of Cyclone as parameters** which maintains performance even if size of Cyclone is huge

Literature Review

TITLE:

Tropical Cyclone Winds Retrieval Algorithm for the Cyclone Global Navigation Satellite System Mission

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
11	10.1109/LGRS.2023.3318187	When compared CYGNSS data with Soil Moisture Active Passive (SMAP) data and found a certain deviation in the CYGNSS ”young sea, limited fetch” (YSLF) data product for high winds.	1) To propose an RF machine learning algorithm for improving the accuracy of CYGNSS wind speed retrieval in tropical cyclones. 2) To explore the impact of different input parameter combinations on model performance	1) The authors compare SMAP data with CYGNSS data and use SMAP data as the "ground truth" to train the RF model for wind speed retrieval 2) They train an RF model using SMAP data as the "ground truth" and apply it to the wind speed retrieval of CYGNSS data	The RF algorithm achieves an RMSE of 2.01 m/s, better than the YSLF accuracy of 6.55 m/s, and eliminates noise in the observed data, providing more accurate wind speed estimates in tropical cyclones.	Suggest exploring further combinations of input parameters and model improvements to enhance wind speed retrieval accuracy.	There is huge Time Consumption as **there are multiple parameters & they all need computation time** , but our Project Extracts features from IR images which is best option in this kind of projects where Time Consumption plays a vital role

Literature Review

TITLE:

Estimating Tropical Cyclone Intensity by Satellite Imagery Utilizing Convolutional Neural Networks

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
12	https://doi.org/10.1175/WAF-D-18-0136.1	The operational **Dvorak techniques** used for estimating tropical cyclone (TC) intensity have deficiencies such as inherent subjectivity and inconsistent intensity estimates within various basins	The researchers aim to improve upon the deficiencies of the operational Dvorak techniques by utilizing a convolutional neural network (CNN) model that directly estimates TC intensity as a regression task.	The CNN model incorporated convolution layers for feature extraction and fully connected layers for transforming features to the target value, which is an estimate of TC intensity. Pooling techniques were also applied to reduce computational complexity.	The performance of the CNN model was evaluated using an independent testing dataset of global TCs, and the results were compared with other techniques such as ADT, AMSU, and SATCON. The CNN-TC model showed promising results with low absolute errors relative to the recon-aided best track intensities	They suggest that future research could focus on refining the model by incorporating additional TC information, **such as basin, day of year, local time, longitude, and latitude**, to further enhance accuracy.	Our research has the potential to bridge the gap by offering a foundation for future studies to expand the scope of CNN models in tropical cyclone prediction by **incorporating additional TC information**.

Literature Review

TITLE :

Tropical Cyclone Intensity Estimation Using Himawari-8 Satellite Cloud Products and Deep Learning with Environmental Field Information

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
13	https://doi.org/10.3390/rs14040812	The author identifies that the performance of the model is highly affected by the initial cloud products used for training.[	The goal of the research is to develop an objective deep-learning-based model for tropical cyclone (TC) intensity estimation using cloud products from the Himawari-8 satellite .	• The research utilizes a convolutional neural network (CNN) as the basic structure for the deep-learning-based model for tropical cyclone (TC) intensity estimation . • The model incorporates residual learning and attention mechanisms to optimize its structure and improve feature extraction ability .	• The model's performance was evaluated using independent test data, showing improvement with a relatively low root mean square error (RMSE) of 4.06 m/s and a mean absolute error (MAE) of 3.23 m/s, comparable to previous studies .	• The authors encourage further research to investigate the model's applicability to other TC metrics, expanding its forecasting capabilities beyond intensity estimation.	

Literature Review

TITLE :

Tropical Cyclone Intensity Probabilistic Forecasting System Based on Deep Learning

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
14	https://doi.org/10.1155/2023/3569538	The problem identified by the authors is the difficulty and bottleneck in intensity forecasting of tropical cyclones (TC) in weather forecasting, which is due to the Earth system's complexity, nonlinearity, and chaotic effects.	The researchers aim to improve upon the deficiencies of the operational Dvorak techniques by utilizing a convolutional neural network (CNN) model that directly estimates TC intensity as a regression task.	Two specific techniques are employed in the research: Bootstrap and Deep Ensemble. Bootstrap is used for resampling the training data to obtain different retraining models, while Deep Ensemble trains multiple neural networks with different parameter initializations on the same data .	our results show that the PTCIF as an intelligent system is expected to complement existing operational models and provide reliable uncertainty prediction intervals that provide powerful insights for risk avoidance and decision-making.	They propose that future research should focus on fully considering the data and uncertainties inherent in the models, rather than solely improving the error performance of the forecasts	

Literature Review

TITLE :

TFG-Net: Tropical Cyclone Intensity Estimation from a Fine-grained perspective with the Graph convolution neural network

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
15	https://doi.org/10.1016/j.engappai.2022.105673	Existing TIE methods **do not adequately consider general wind speed information**, focusing primarily on image recognition. Existing methods categorize objects into broader categories instead of finer categories, which is essential for accurately estimating cyclone intensity.	The goal of the research is to improve the accuracy of TIE by considering fine-grained categorization and incorporating general wind speed information.	Development of TFG-Net with three key components: Backbone, Fine-grained Tropical cyclone Features Extractor (FTFE), and Wind Scale Transition Rule Generator (WTRG) for extracting spatial features, subtle features, and wind speed information, respectively.	The authors concluded the solution to the problem of Tropical Cyclone Intensity Estimation (TIE) by proposing a novel model called Tropical cyclone intensity estimation from a Fine-grained perspective with the Graph convolution neural Network (TFG-Net).	Suggest future research to develop a time-series version of TFG-Net that considers the correlation between target wind speed and historical tropical cyclone satellite images for improved prediction accuracy.	

Literature Review

TITLE :

A CNN-Based Hybrid Model for Tropical Cyclone Intensity Estimation in Meteorological Industry

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
16	10.1109/ACCESS.2020.2982772	The authors mention that TC intensity estimation is challenging because it requires domain knowledge to manually extract TC cloud structure features and form various sets of parameters obtained from satellites.	The goal is to improve the fitting speed on small samples by using piecewise regression and to correct the negative impact caused by piecewise regression using other models. The research also aims to achieve high accuracy and low root-mean-square error (RMSE) in TC intensity estimation by using inferred images.	The authors divide TCs into three types and use three different models for intensity regression. They also use piecewise regression to improve the fitting speed on small samples and correct its negative impact using other models.	The authors concluded that their hybrid model based on CNNs improved the accuracy of TC intensity estimation and outperformed traditional meteorological methods.	The authors imply that there is scope for further research and enhancement in the field of TC intensity estimation using CNN-based models, particularly in improving accuracy and exploring new applications	

Literature Review

TITLE :

A Novel Deep Learning Framework for Tropical Cyclone Intensity Estimation Using FY-4 Satellite Imagery

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
17	https://doi.org/10.1145/3390557.3394298	The problem addressed in this study is the challenging task of accurately estimating tropical cyclone (TC) intensity using multispectral images from China's FY-4 Satellite.	The goal is to achieve high intensity classification accuracy and low wind speed estimation errors for MSIs of different spectral dimensions. The research aims to address the challenging task of TC intensity estimation and provide a reliable and accurate method for estimating TC intensity using satellite imagery.	The framework combines a Coupled Convolutional Neural Network **(Coupled CNN)** for intensity categorization and Classwise Regressors for wind speed estimation.	**By sharing the weights** between the two parallel CNNs in the Coupled CNN, the framework reduces the disparity of accuracy and **avoids overfitting.** The Class-wise Regressors achieve high estimation accuracy by making full use of the reliable results of the Coupled CNN.	The author suggests that for further research, they will study end-to-end methods that could estimate wind speed directly without applying classification at first.	

Literature Review

TITLE :

Deep Learning Experiments for Tropical Cyclone Intensity Forecasts

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
18	https://doi.org/10.1175/WAF-D-20-0104.1	The problem identified by the authors is the challenge of reducing tropical cyclone (TC) intensity forecast errors, which has interested the operational forecasting and research community for decades.	The researchers aim to address the challenge of reducing TC intensity forecast errors and improve operational hurricane intensity forecasts by developing a deep learning-based model for tropical cyclone intensity forecasts.	The researchers developed a deep learning-based multilayer perceptron (MLP) model for tropical cyclone intensity forecasts. The model was trained using the global Statistical Hurricane Intensity Prediction Scheme (SHIPS) predictors to forecast the change in TC maximum wind speed for the Atlantic basin.	The MLP model outperformed other statistical-dynamical models by 9%-20% in the 24-hour intensity forecast experiment, as well as by 5%-22% in the real-time operational forecast simulations for 2019 and 2020.	The authors suggest that the MLP-based intensity models can be further improved by extending the deep learning architecture search to beyond five hidden layers, which may result in deeper and more powerful models.	

Literature Review

TITLE :

Deep Learning Based Cyclone Intensity Estimation using INSAT - 3D IR Imagery -comparative study

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
19	https://ijrpr.com/uploads/V4ISSUE4/IJRPR12056.pdf	The problem addressed in this study is the Accurate and timely estimation of tropical cyclone intensity is crucial for minimizing damage and saving lives during extreme weather events.	The study aims to evaluate three different models - a convolutional neural network (CNN), a recurrent neural network (RNN), and a combination of both (CNN-RNN) - for their ability to accurately predict cyclone intensity based on IR imagery.	• Three different deep learning models are evaluated: a convolutional neural network (CNN), a recurrent neural network (RNN), and a combination of both (CNN-RNN). • The performance of these deep learning models is compared with traditional machine learning algorithms such as support vector machines (SVM) and random forests (RF).	The developed solution has the potential to significantly improve the accuracy and reliability of cyclone intensity estimation, potentially aiding in the reduction of chaos and abnormalities caused by tropical cyclones.	Investigating the use of additional meteorological data, such as wind speed and atmospheric pressure, in combination with IR imagery, to improve the accuracy of cyclone intensity estimation .	

Literature Review

TITLE:

DMANet_KF: Tropical Cyclone Intensity Estimation Based on Deep Learning and Kalman Filter From Multispectral Infrared Images

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
20	10.1109/JSTARS.2023.3273232	The problem addressed in this study is utilizing a local global attention module to make the model focus on local key features (i.e., the typhoon eye) and obtain deeper global semantic information of TC.	The paper aims to address the challenges in TC intensity estimation, such as effectively utilizing multispectral data, preserving the important feature of the typhoon eye, and improving the accuracy of intensity estimation without inappropriate smoothing.	the proposed model is a convolutional neural network (CNN) that can effectively utilize the available data and provide accurate TC intensity estimates.	the paper applies Kalman filter to modify the time-series estimation results, resulting in a decrease in RMSE from 9.79 to 7.82 knots and MAE from 7.52 to 6.19 knots. The applicability of Kalman filter in TC intensity estimation is confirmed.	The proposed DMANet model can be further optimized by exploring different network architectures or incorporating advanced techniques, such as attention mechanisms or recurrent neural networks, to capture more complex temporal dependencies in TC intensity estimation.	

Literature Review

TITLE:

Global Tropical Cyclone Precipitation Estimation via a Multitask Convolutional Neural Network Based on HURSAT-B1 Data

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
21	10.1109/TGRS.2021.3126419	Difficulty in accurately estimating tropical cyclone (TC) precipitation due to limited high spatiotemporal observations.	proposed model obtains a more consistent and continuous spatial distribution of precipitation than MLR and RF. The model can achieve high spatiotemporal results, which has the potential to serve as an operational algorithm for global TC precipitation estimation.	Core components: feature extraction, wind grade classification, and precipitation estimation modules. Outperforms other models in most metrics and provides more consistent spatial distribution of precipitation.	The TC precipitation estimation model (TCPRENET) based on multitask CNN outperforms other models such as MLR, RF, SDAEs, and cGANs in terms of estimation performance .	Future work should consider using GEO satellite observations for improved timeliness, assigning different weights for precipitation estimates within different thresholds, and introducing loss functions like SSIM to reduce estimation errors.	

Literature Review

TITLE:

Tropical Cyclone Forecast Using Multitask Deep Learning Framework

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
22	10.1109/LGRS.2021.3132395	Difficulty in accurately forecasting tropical cyclone (TC) path and intensity due to complex factors affecting TC motion and limited understanding of intensity changes.	The objective of the paper is to propose a flexible and reliable tropical cyclone forecasting framework that can simultaneously forecast the path and intensity of tropical cyclones using a set of data	The paper introduces two models, WCycleGAN and TIENet, which enhance the effectiveness of the forecasting framework. WCycleGAN is a new model that handles unpaired images, while TIENet is a specialized model for interpreting predicted tropical cyclone images	This framework is scalable and can handle multiple tasks at the same time, making it useful in situations where computing resources or professional meteorological knowledge is lacking .	Future research can explore the use of various data inputs, such as satellite images and meteorological reanalysis data, and different TC data analysis models. Further improvements in path and intensity forecasting accuracy and the application of the proposed framework with limited computing resources or meteorological expertise.	

Literature Review

TITLE:

Infrared and Visible Image Fusion Techniques Based on Deep Learning

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
23	https://doi.org/10.3390/electronics9122162	The study explores the use of deep learning methods for fusing infrared and visible images to enhance fusion quality and efficiency, addressing the need for improved image fusion techniques in various applications.	the objective of the paper is to provide a comprehensive overview of the development, evaluation, and future prospects of image fusion algorithms based on deep learning, specifically focusing on infrared and visible image fusion	The authors review the infrared and visible image fusion methods based on deep learning, including methods based on convolutional neural network (CNN), generative adversarial networks (GAN), Siamese network, and autoencoder .	Deep learning methods have improved the efficiency and effectiveness of image fusion, but there is a need for further development and optimization in various application scenarios.	The loss of visible image information is identified as a critical problem that can lead to image fusion failure, emphasizing the importance of addressing this issue in future research	

Literature Review

TITLE :

Estimation of global tropical cyclone wind speed probabilities using the STORM dataset

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
24	https://doi.org/10.1038/s41597-020-00720-x	The problem addressed in this study is the need for accurate estimation of tropical cyclone wind speed return periods to assess TC-related hazards, where traditional distribution-based methods tend to overestimate wind speeds for longer return periods, and the study offers a solution using the STORM dataset for empirically derived estimates.	To estimate global tropical cyclone wind speed probabilities using the STORM dataset and empirical RP method.	**The STORM model takes various parameters from the IBTrACS data, such as the latitudinal and longitudinal position of the TC, maximum 10-meter 10-minute average sustained wind speeds, mean sea-level pressure, and the size of the TC eye.**	The study calculates return periods empirically and compares them with five extreme value distributions, taking into account TC tracks and wind field characteristics.	The paper suggests that future research should focus on improving the representation of asymmetry in the TC wind field, particularly in extratropical regions where enhanced wind shear may induce asymmetry.	

Literature Review

TITLE :

TROPICAL CYCLONE INTENSITY ESTIMATIONS OVER THE INDIAN OCEAN USING MACHINE LEARNING

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
25	https://arxiv.org/pdf/2107.05573	The problem addressed in this study is the accurate estimation of tropical cyclone intensity, including grade and maximum sustained surface wind speed (MSWS), over the North Indian Ocean using machine learning algorithms to enhance predictions for disaster preparedness and response.	To estimate tropical cyclone intensity over the Indian Ocean using machine learning regression and classification algorithms.	Utilization of machine learning algorithms for predicting maximum sustained surface wind speed (MSWS) and grade of tropical cyclones.	The study employs a variety of machine learning algorithms to predict MSWS and grade, considering MSWS as a continuous variable and grade as a categorical variable.	Explore methods to standardize and unify parameter calculations for practical implementation. Investigate the integration of image datasets for enhanced accuracy.	

Literature Review

TITLE:

Quality Estimates of INSAT-3D Derived Cloud Top Temperature for Climate Data Record

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
26	10.1109/TGRS.2020.3022680	Need for reliable cloud top temperature (CTT) measurements for climate research and evaluation of cloud-resolving models.	To **evaluate the quality of INSAT-3D-derived CTT products at 4 km and 50 km resolutions** in terms of GCOS requirements by validating them with ground-based hyper-spectral microwave radiometer (MWR) measurements.	Quality assessment of INSAT-3D retrieved CTT is carried out by comparing it with the CTT derived from ground-based hyper-spectral microwave radiometer (MWR) for a period of 1 year	1) MWR shows uncertainty of 3.96 and 5.01 K respectively for INSAT-3D CTT at 4 and 50 km, which are close to the GCOS standard uncertainty range of 1–5 K. 2) INSAT-3D CTTs at 4 and 50 km shows an overall MAE and RMSE 7.22 and 11.82 K respectively.		

Literature Review

TITLE:

Single-Pass Tropical Cyclone Detector and Scene-Classified Wind Speed Retrieval Model for Spaceborne GNSS Reflectometry

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
27	10.1109/TGRS.2023.3253564	The problem addressed in the paper is the traditional approach of developing a GMF (Gain Modulation Function) model for wind speed retrieval is not suitable for tropical cyclones due to the different dependences of the DDMA (Delay-Doppler Mapping Algorithm) and LES (Large Eddy Simulation) on wind speed in cyclone conditions compared to fair-weather conditions.	The research aims retrieval of wind speed in tropical cyclones using spaceborne GNSS-R data.	1) Determining sea conditions using Frequency-Domain Delay Maps (FDDMs) from a specular point trajectory. 2) Using different Gain Modulation Functions (GMFs) for cyclone and cyclone-free conditions based on the detected sea conditions.	The DDM asymmetry is sensitive to the wind speed field in tropical cyclones. The proposed detector provides good performance for detecting tropical cyclones when the distance between the specular point trajectory and cyclone center is less than 100 km. The proposed retrieval model improves wind speed estimation, especially in cyclone conditions.		

Literature Review

TITLE :

Tropical Cyclone Intensity Estimation Using Temporal And Spatial Features From Satellite Data

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
28	https://digital.library.ncat.edu/cgi/viewcontent.cgi?article=1120&context=dissertations	The problem addressed in this study is the accurate estimation of tropical cyclone (TC) intensity using historical satellite images, focusing on the development of an automated algorithm that combines temporal and spatial features to improve intensity predictions, thus enhancing the reliability of TC intensity forecasts for economic and safety purposes.	To Develop an automated method to estimate tropical cyclone (TC) intensity using historical satellite images alone	Utilize Hurricane Satellite data for TC intensity estimation, focusing on the North Atlantic from 1978-2009	The results show that the accuracy for averaging the intensities of the 10 NNs and averaging the intensities of the NNs within a radius of 13% of the maximum possible distance are very close.	Future research can explore additional data sources, refine the algorithm, and expand its applicability to other regions	

Literature Review

TITLE:

Anomaly detection in thermal images using deep neural networks

S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
29	10.1109/ICIP.2017.8296692	Manual detection is time-consuming and unreliable, making it unable to meet the excessive demand for condition monitoring in industrial applications	To propose an automatic anomaly detection method in thermal images using deep neural networks (DNNs) to improve efficiency and reliability in electrical preventive maintenance.	Utilization of DNNs for learning statistical regularities in normal thermal images and pixel-wise comparison for anomaly detection.	The proposed method demonstrates its effectiveness in detecting thermal anomalies in electrical equipment.	**Incorporating adversarial loss** in training the model may reduce the blurring effect and produce higher quality prediction	

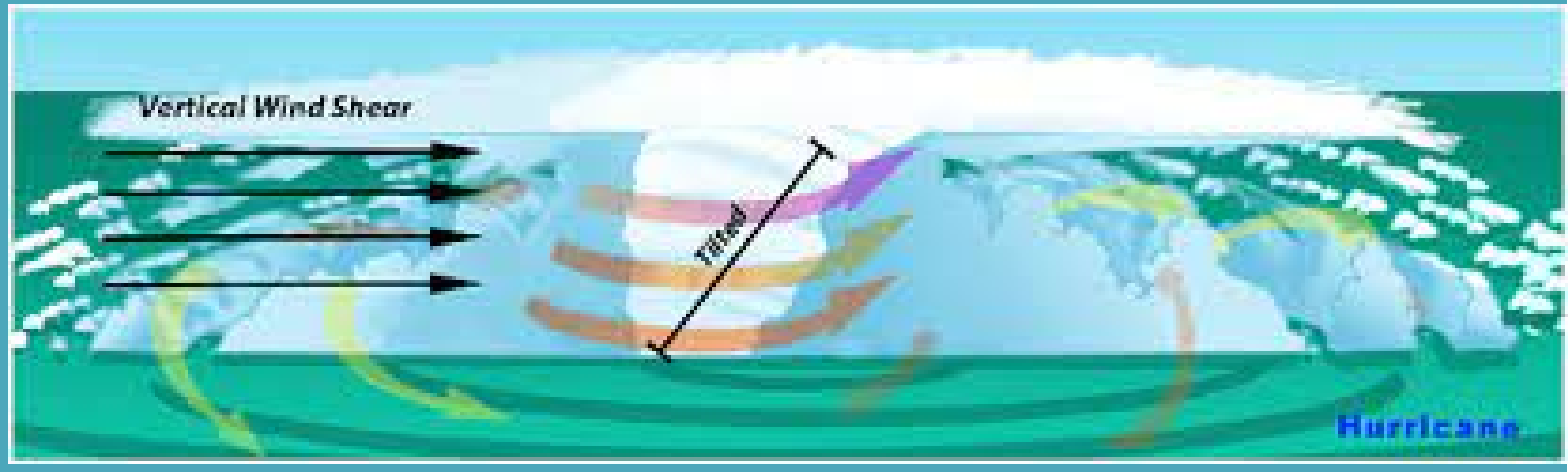
Literature Review

TITLE :

Attention-based Deep Tropical Cyclone Rapid Intensification Prediction

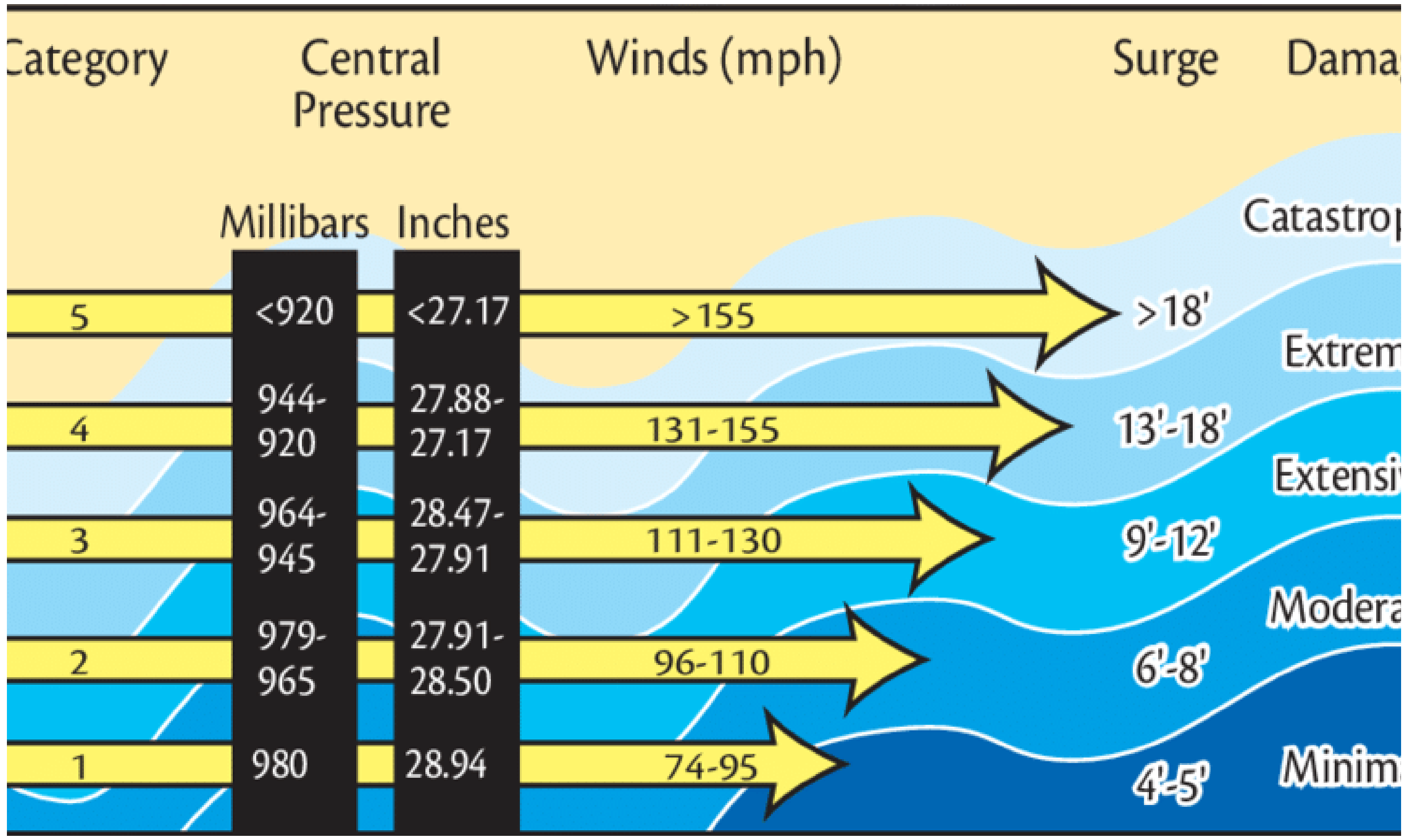
S.NO	Reference with DOI	Problem addressed	Objective of the research	Focus of the paper (Methods used)	inference (Conclusion Given by Authors)	Recommendations for future research	how can your research help bridge the gap
30	https://ceur-ws.org/Vol-2466/paper2.pdf	The problem addressed in this study is the accurate and early prediction of rapid intensification (RI) in tropical cyclones, which is challenging and requires effective feature extraction, and the study explores the use of deep learning models for this purpose.	The goal of the paper is to evaluate the potential use of deep learning models for predicting rapid intensification (RI) in tropical cyclones (TCs) using TC images.	methodology is designed to prevent overfitting on the small dataset and is inspired by the Advanced Dvorak Technique (ADT), which is the most widely used method for TC intensity prediction	Best performing model for BSS is the self-attention variant (43 % improvement), and the best for HSS is the combined variant (11 % improvement)	Investigate improved designs for attention mechanisms tailored for RI prediction. Explore data augmentation techniques, such as generative adversarial networks, for enhanced model robustness.	

Existing System

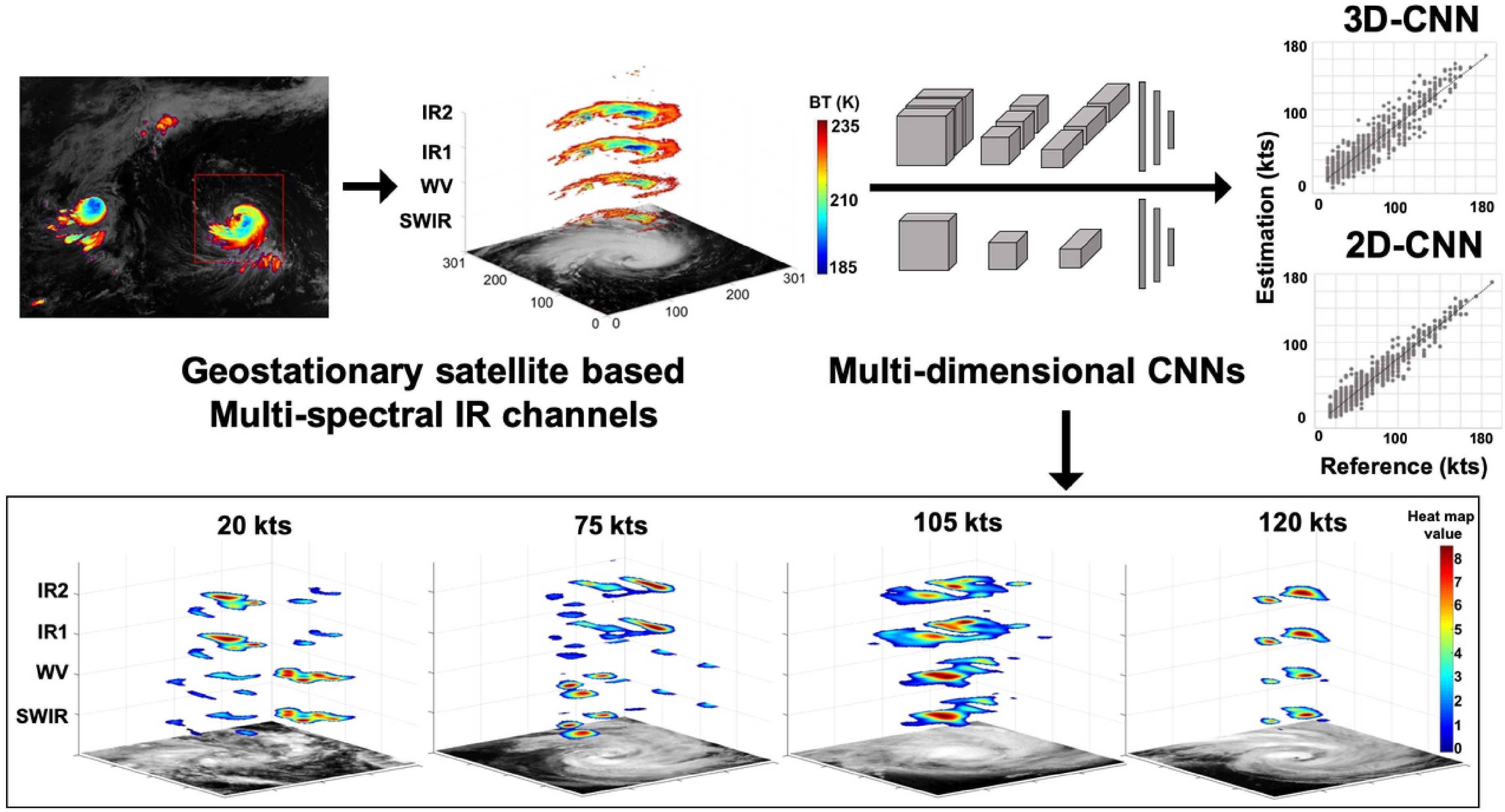


The existing system for cyclone intensity estimation relies on traditional methods like aerial reconnaissance and weather stations, which are time-consuming and prone to human errors.

The existing model that is used by ISRO for cyclone intensity estimation in the HWRF model, which has some disadvantage.



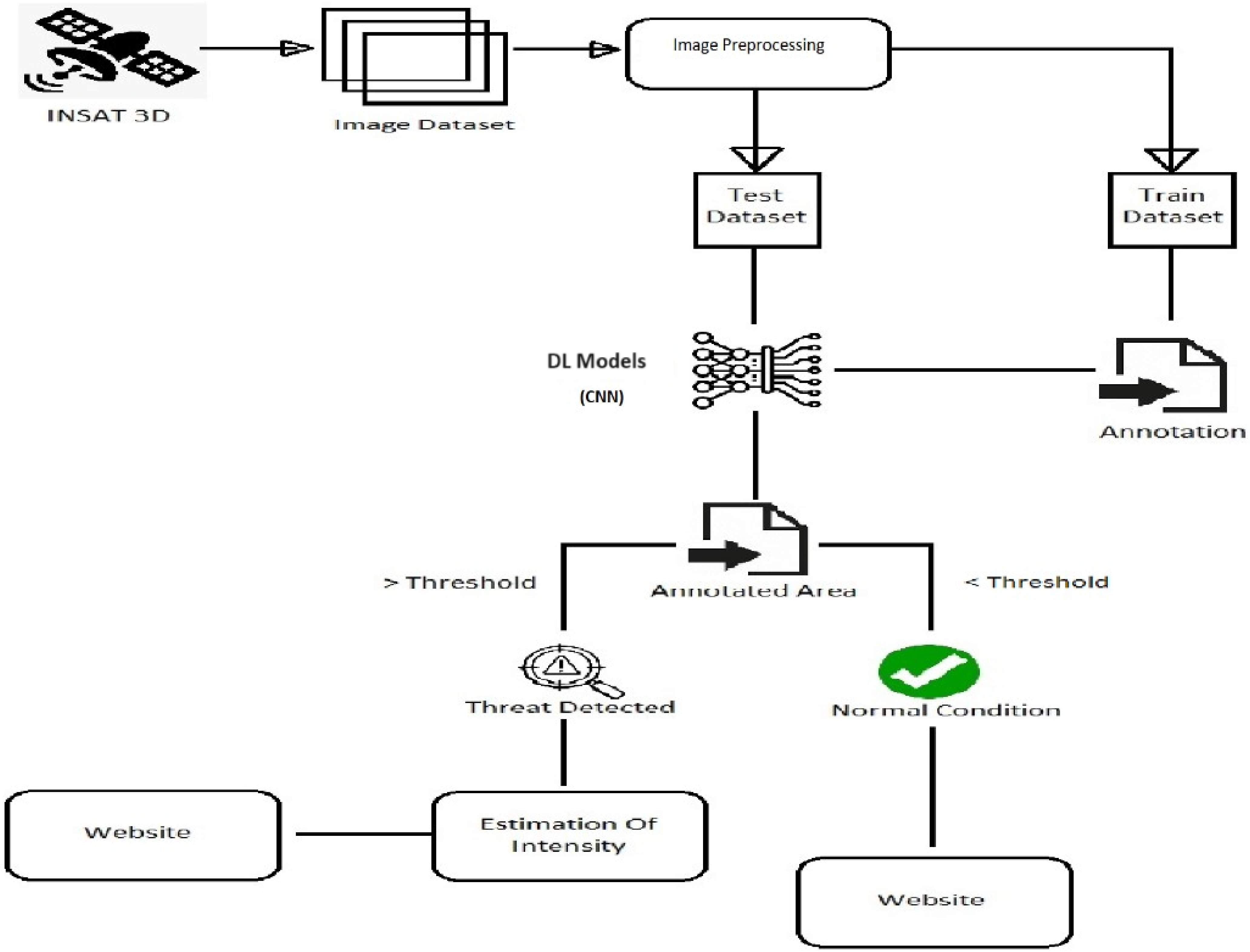
Proposed System



3D CNN-based activated regions by TC intensity

The proposed system utilizes deep learning, specifically CNNs, to automate cyclone intensity estimation from INSAT-3D IR imagery. In INSAT-3D observations are available at every 30 minutes intervals. The real-time inference pipeline enables quick predictions during active cyclonic events. Performance evaluation and error analysis ensure the system's accuracy and reliability.

System Architecture



Modules

- **Intensity Estimation Module :**

Estimates the cyclone's intensity (in knots) based on satellite images using a trained deep-learning model.

- **Direction Detection Module :**

Determines the direction of cyclone movement (East, West, North, South) by analyzing satellite imagery with a deep-learning model.

- **User Interface Module :**

Provides an interactive interface for users to upload images, and obtain intensity and direction predictions for cyclones.

System Requirements

Software requirements

- VS Code
- Jupiter Notebook
- Anaconda Prompt

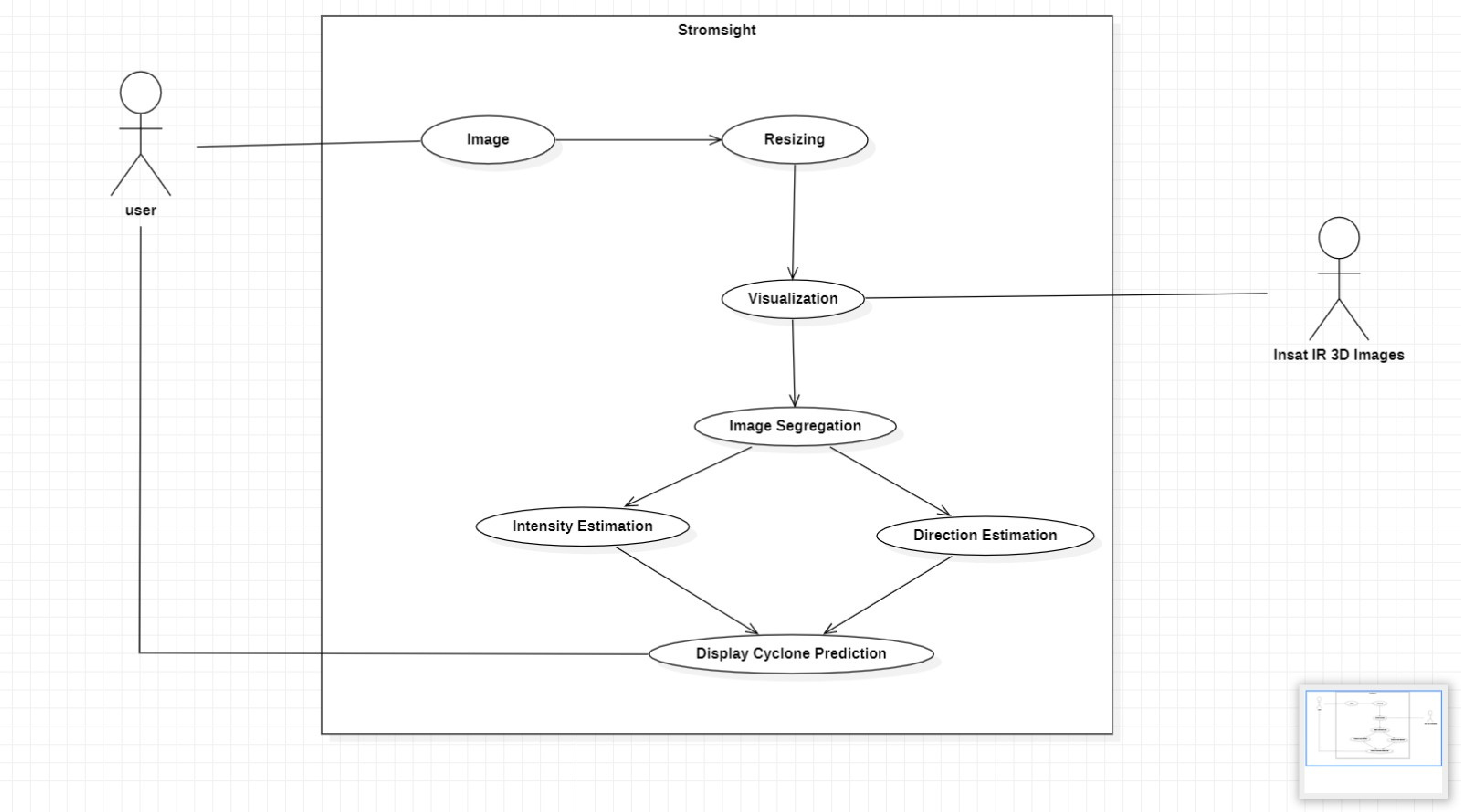
Technologies requirements

- Html
- CSS
- Python
- Numpy
- Pandas
- Tenserflow

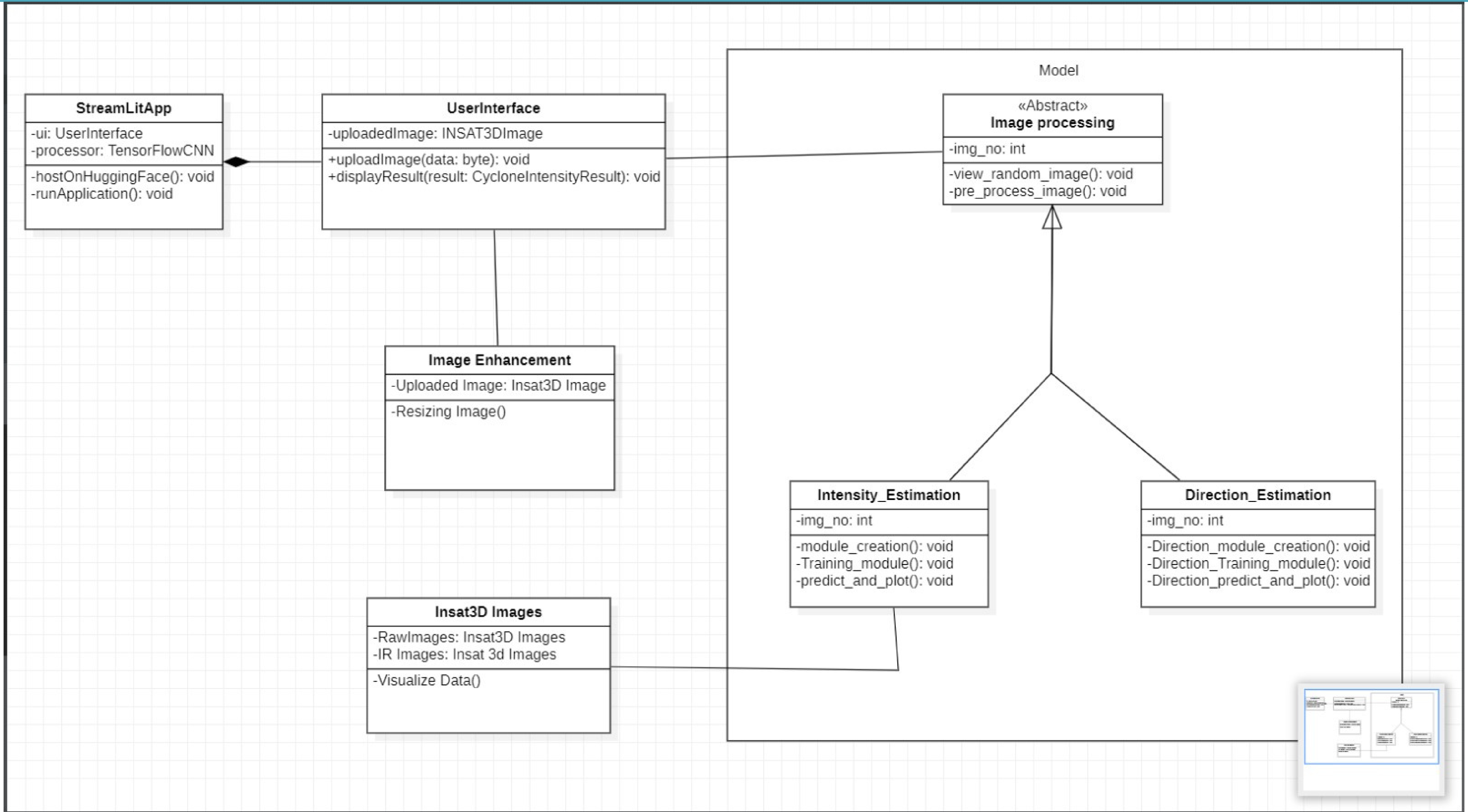
Scope / Objectives

- To Extract Features from Pre-Processed Dataset.
- To Build a CNN Model and Train the model using Pre-Processed Data.
- To Design a User Interface & Integrate the Model with it, which Estimates the Cyclone Intensity by taking Image as an Input.

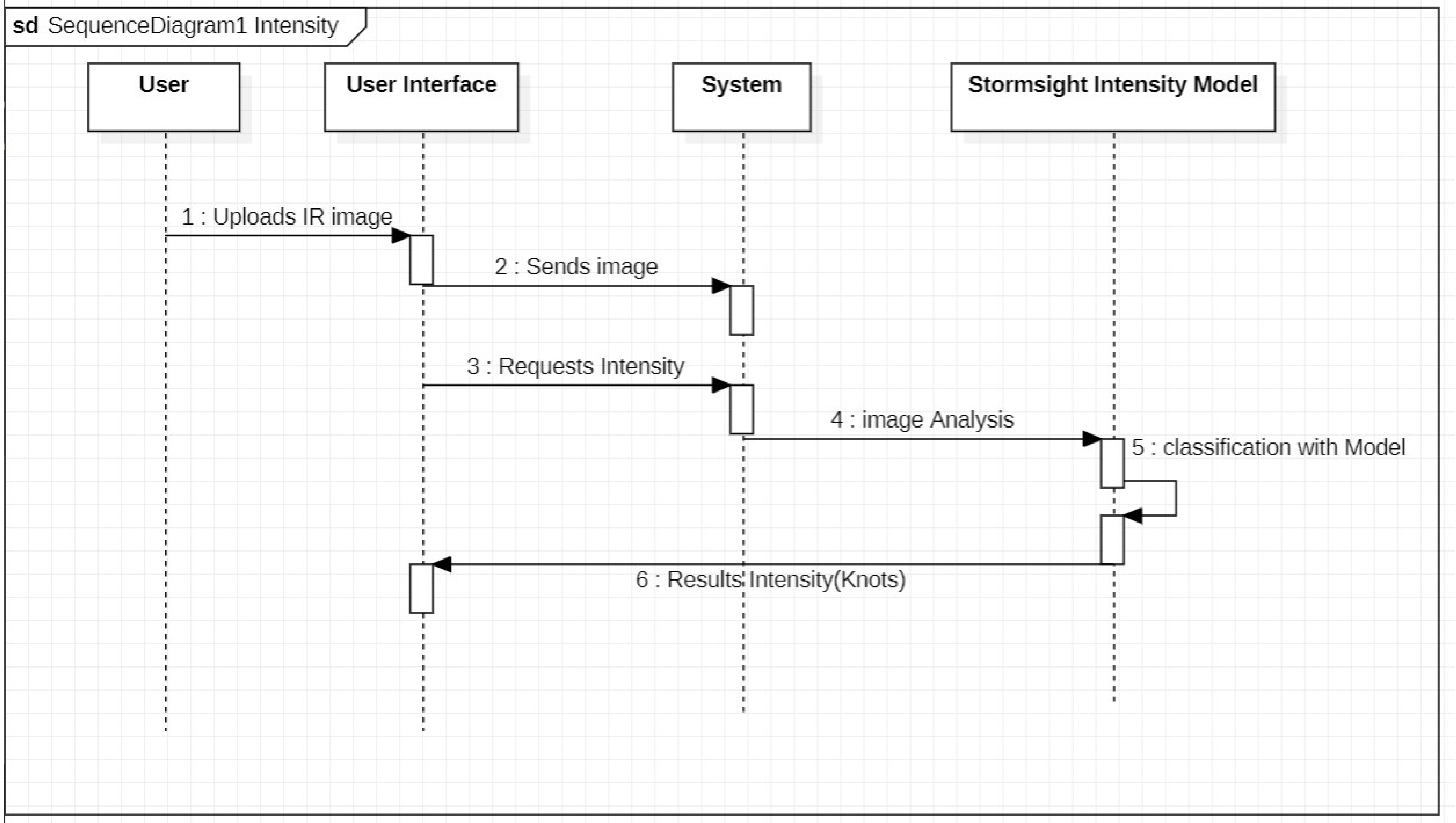
UML Diagrams (UseCase)



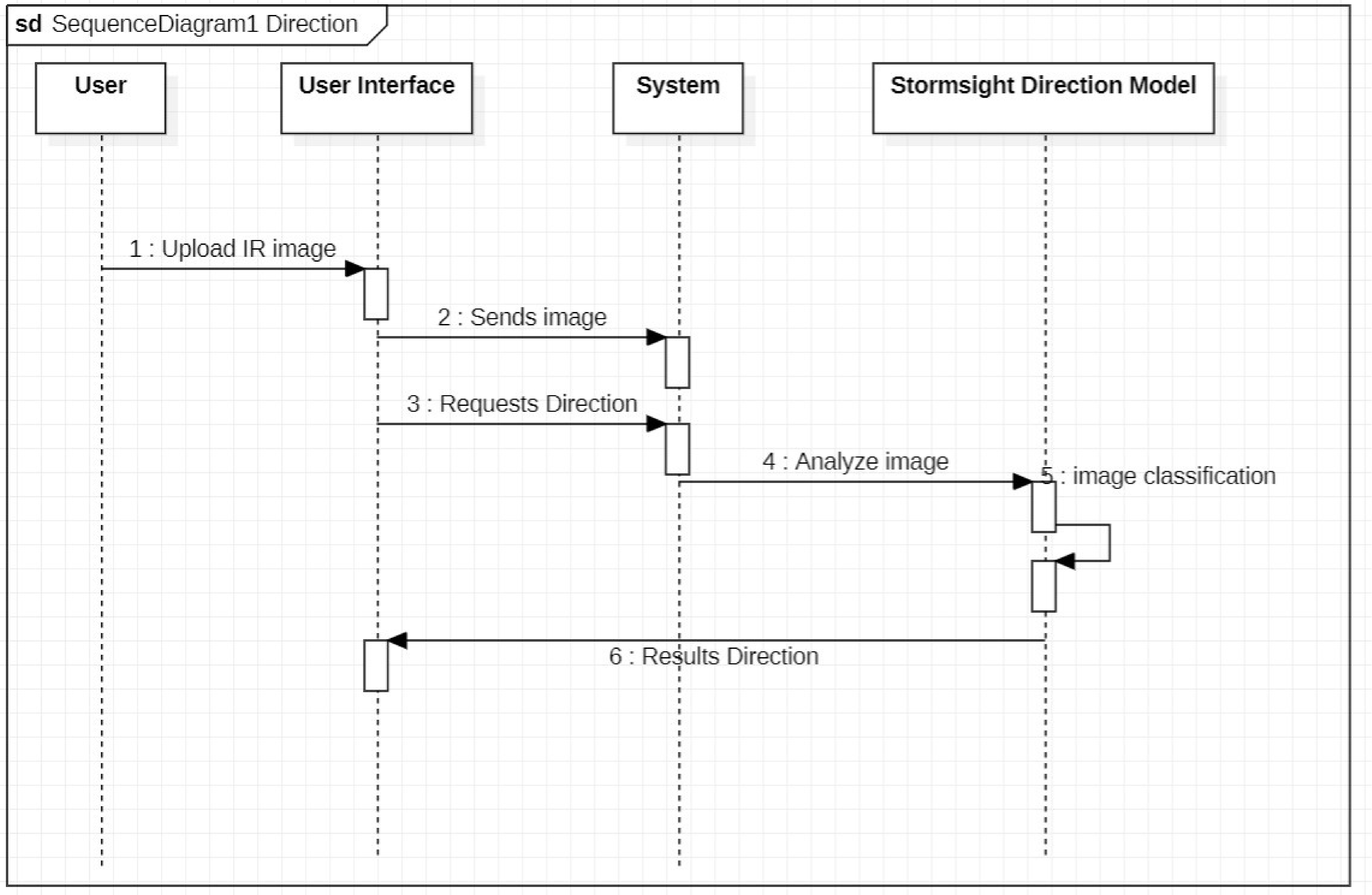
UML Diagrams (Class)



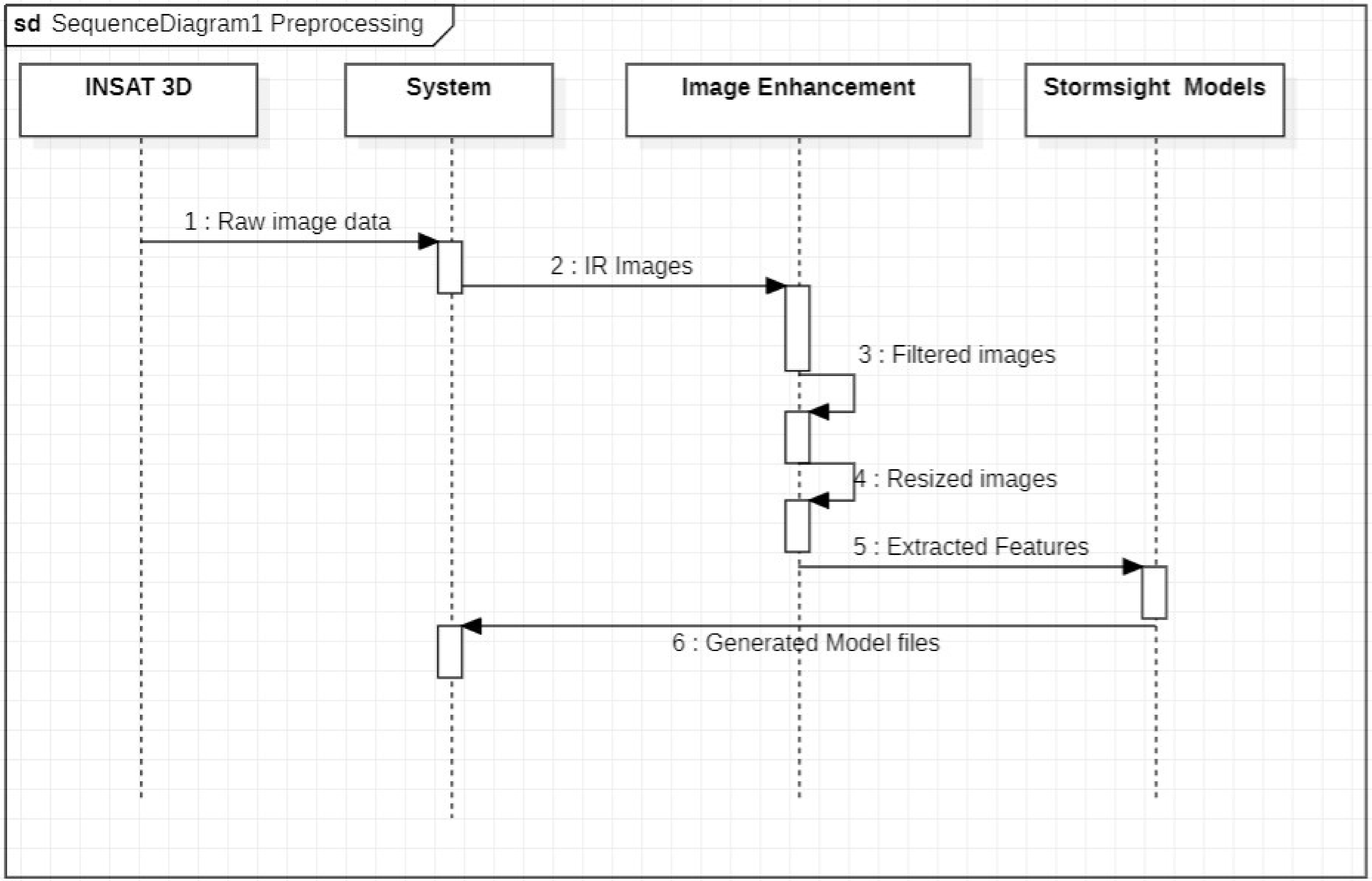
UML Diagrams (Sequence)



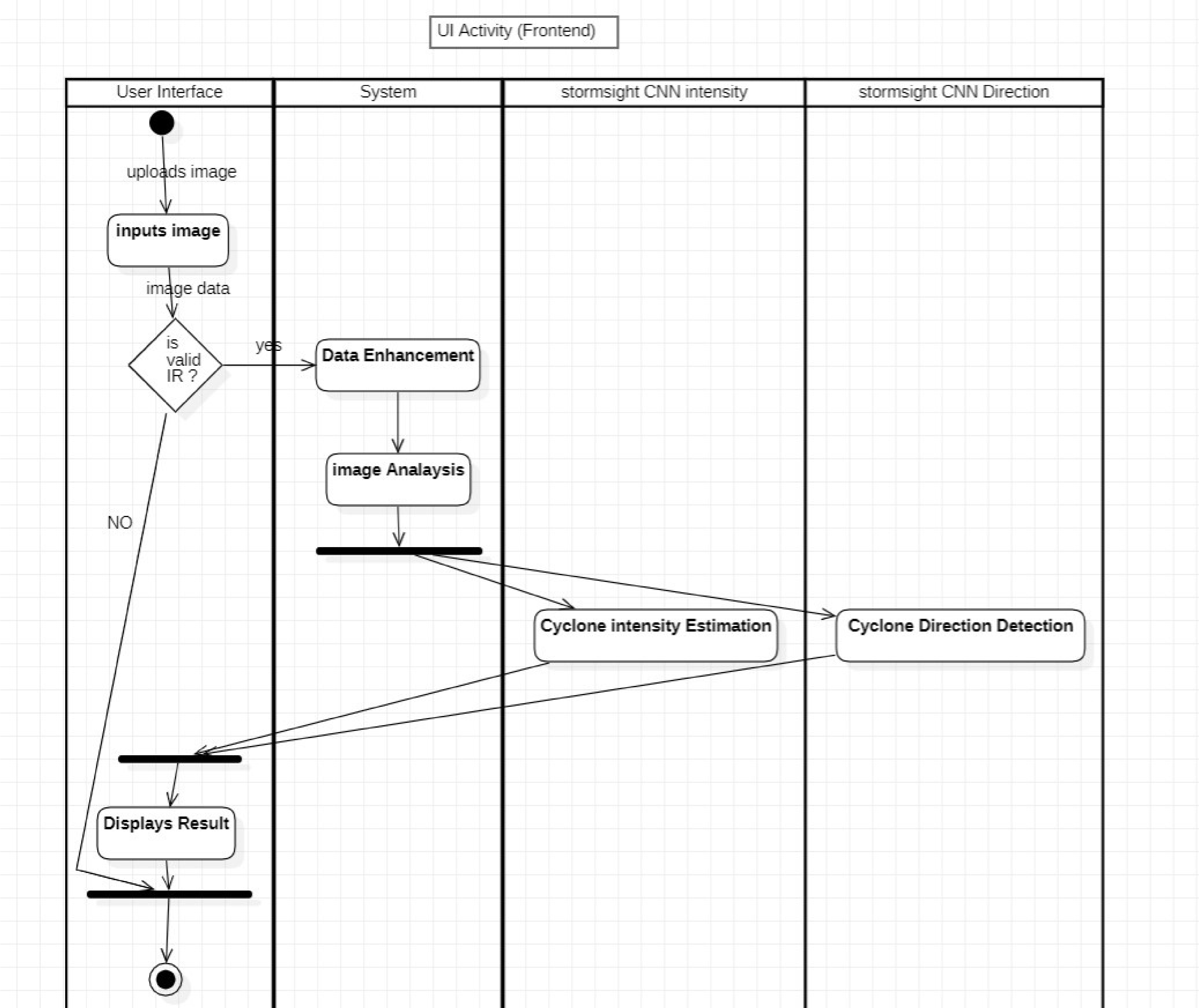
UML Diagrams (Sequence)



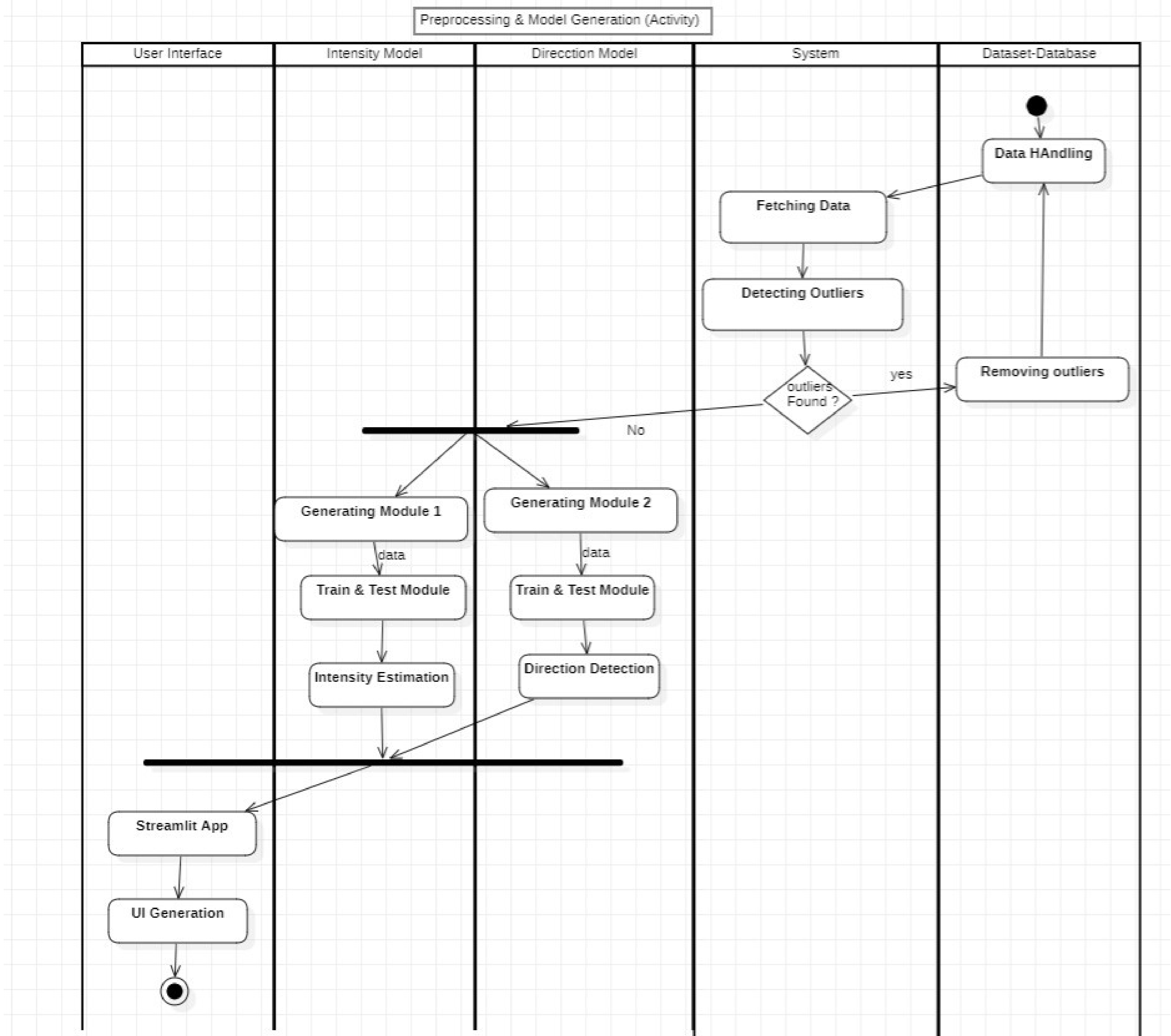
UML Diagrams (Sequence)



UML Diagrams (Activity)



UML Diagrams (Activity)



Algorithm (Main Module)

```
Step 1: Load Dataset:
        Call the load_dataset() function to load the dataset.

Step 2: View Random Images from 'test_data' directory:
        Call the view_random_image('test_data') function to display random images from the 'test_data' directory.

Step 3: Create Model:
        Call the create_model() function to create the neural network model.

Step 4: Display Model Summary:
        Call the appropriate function to display the summary of the created model.

Step 5: Compile Model:
        Call the compile_model() function to compile the created model.

Step 6: Fit Model with training data (train_data):
        Call the fitting_model() function to train the compiled model using the training data.

Step 7: Predict and Plot results for image "img/path":
        Specify the filename or path of the image for prediction.
        Call the pred_and_plot(model, filename) function to predict and plot results for the specified image.
```

Algorithm (Load Dataset Module)

Step 1: Set Source and Destination Paths:

- Set the source directory path as source='insat3d_ir_cyclone_ds/CYCLONE_DATASET_INFRARED'.
- Set the destination directory path as destination='test_data'.

Step 2: List All Files in Source Directory:

- Use allfiles=os.listdir(source) to get a list of all files in the source directory.

Step 3: Move Files to Destination Folder:

- Iterate through each file f starting from the 134th index of allfilesallfiles:
- Construct the source and destination paths:
- src_path=os.path.join(source,f)
- dst_path=os.path.join(destination,f)
- Move the file from the source to the destination using:
- shutil.move(src_path,dst_path)shutil.move(src_path,dst_path).

Algorithm (View Image Module)

Algorithm for the view random image function.

Step 1: Set Target Folder:

- Set the target directory containing images as target_folder.

Step 2: Randomly Sample Images:

- Use random_image=random.sample(os.listdir(target_folder),10) to randomly select 10 images from the target folder.

Step 3: Display Images:

- Create a figure using plt.figure(figsize=(10, 10)) to set the size of the plot.
- Iterate through each randomly selected image index i from 0 to 9:
- Load the image using img=mpimg.imread(os.path.join(target_folder,random_image[i])).
- Create a subplot using plt.subplot(5,2,i+1) to arrange the images in a grid.
- Display the image using plt.imshow(img).
- Set the title of the subplot as the image filename using plt.title(random_image[i]).
- Turn off the axis using plt.axis("off") to remove the axis labels.

Algorithm (Create Model Module)

Step 1: Initialize Input Layer:

- Initialize the input layer with the shape (256,256,3) representing 256×256 pixels with 3 color channels (RGB).

Step 2: Define Layers:

- Define the layers as Layers=[Conv2D(256),Conv2D(256),MaxPool2D,…,Conv2D(16),MaxPool2D].

Step 3: Iterate through Layers:

For each layer layer in Layers:

- Apply Convolutional layer:
  - Use Convolution(layer) to apply a convolutional layer with specified parameters such as filters, kernel size, initializer, regularization, activation, and padding.
- Apply Batch Normalization:
  - Use BatchNorm(layer) to apply batch normalization.
- Apply ReLU Activation:
  - Use ReLU(layer) to apply rectified linear unit activation function.
- If the layer is a MaxPooling layer:
  - Apply MaxPooling operation.

Step 4: Flatten Output:

- Flatten the output from the last convolutional block to prepare it for the fully connected layers.

Step 5: Generate Output Prediction:

- Generate output prediction using a Dense layer with 1 neuron and linear activation.

Step 6: Regularization:

- Apply L1L2 regularization to each Convolutional layer.

Step 7: Construct and Return Model:

- Construct and return the model with the input and output layers.

Algorithm (Compile Model Module)

Step 1: Define Loss Function, Optimizer, and Metrics:

- Specify the loss function, optimizer, and evaluation metrics to be used for training the model.
- Define the loss function as Mean Squared Error (MSE),
  - e.g., `loss=tf.keras.losses.MSE`.
- Choose an optimizer, such as Adam, and specify its learning rate,
  - e.g., `optimizer=tf.keras.optimizers.Adam(lr=0.002)`.
- Specify metrics for evaluation,
  - e.g., `metrics=["mse"]`.

Step 2: Compile the Model:

- Compile the model using the compiled function provided by the deep learning framework,
  e.g., `model.compile(loss=loss,optimizer=optimizer,metrics=metrics)`.

Step 3: Define Early Stopping:

- Optionally, define early stopping criteria to prevent overfitting

Algorithm (Fitting Model Module)

Step 1: Train the Model:

- Train the compiled model using the training data.
- Specify the number of epochs and callbacks, if any.
- Use model.fit(train_data,epochs=50,callbacks=[early_stopping]) to start the training process.

Step 2: Monitor Training Progress:

- During training, the model's performance metrics and loss function values are monitored.
- If early stopping is implemented,
  the training process may stop early if the specified criteria are met.

Step 3: Return Training History:

- Return the training history,
  which typically includes metrics such as loss and accuracy values over epochs.

Algorithm (Load and Prep Module)

Step 1: Read Image File:

- Read the image file specified by the filename using img=tf.io.read_file(filename).

Step 2: Decode Image:

- Decode the image using img=tf.image.decode_image(img,channels=3) to ensure the image is properly decoded with three color channels (RGB).

Step 3: Resize Image:

- Resize the image to a specified size, e.g., 256×256 pixels, using img=tf.image.resize(img,size=[256,256]) to ensure consistency in dimensions.

Step 4: Normalize Pixel Values:

- Normalize the pixel values of the image to the range [0,1] by dividing each pixel value by 255, e.g., img=img/255..

Step 5: Return Preprocessed Image:

- Return the preprocessed image img.

Algorithm (Pred and Plot Module)

Step 1: Load and Preprocess Image:

- Call the "Load and Prep Image" function to load and preprocess the image specified by the filename.

Step 2: Make Prediction:

- Use the trained model to predict the output for the preprocessed image.
- pred=model.predict(tf.expand_dims(img,axis=0)) to get the prediction result.

Step 3: Display Image and Prediction:

- Display the original image using matplotlib, e.g., plt.imshow(img).
- Set the title of the plot to include the prediction, e.g., plt.title("Prediction: "+str(pred)).
- Disable axis using plt.axis("off") to remove axis labels.

Step 4: Show Plot:

- Display the plot using plt.show().

Pseudo code

```
Function main():
    Load Dataset
    View Random Images from 'test_data' directory
    Create Model
    Display Model Summary
    Compile Model
    Fit Model with training data (train_data)
    Predict and Plot results for image "img/path"

Main Function End
```

Pseudo code

```
Function load_dataset():
    source = 'insat3d_ir_cyclone_ds/CYCLONE_DATASET_INFRARED'
    destination = 'test_data'

    # gather all files
    allfiles = os.listdir(source)

    # iterate on all files to move them to destination folder
    for f in allfiles[133:]:
        src_path = os.path.join(source, f)
        dst_path = os.path.join(destination, f)
        shutil.move(src_path, dst_path)

Load Dataset Function End
```

Pseudo code

```
Function view_random_image(target_dir):
    target_folder = target_dir
    random_image = random.sample(os.listdir(target_folder), 10)
    plt.figure(figsize=(10, 10))
    for i in range(10):
        img = mpimg.imread(os.path.join(target_folder, random_image[i]))
        plt.subplot(5, 2, i + 1)
        plt.imshow(img)
        plt.title(random_image[i])
        plt.axis("off")

View Random Image Function End
```

Pseudo code

```
Function create_model():
    Initialize input layer with shape (256, 256, 3)
    Layers = [  Conv2D(256), Conv2D(256), MaxPool2D,
                Conv2D(256), Conv2D(128), MaxPool2D,
                Conv2D(128), Conv2D(64), MaxPool2D,
                Conv2D(64), Conv2D(32), MaxPool2D,
                Conv2D(32), Conv2D(16), MaxPool2D   ]
    For each layer in Layers:
        Apply Convolutional layer with specified filters,
                                       kernel size 3x3,
                                       He normal initializer,
                                       L1L2 regularization (0.01),
                                       ReLU activation,
                                       padding same
        Apply Batch Normalization
        Apply ReLU activation

        If layer is MaxPool2D:
            Apply MaxPooling with default parameters

    Flatten the output from the last convolutional block
    Generate output prediction using a Dense layer with 1 neuron and linear activation
    Apply L1L2 regularization to each Convolutional layer
    Construct and return the model with the input and output layers

Create Model Function End
```

Pseudo code

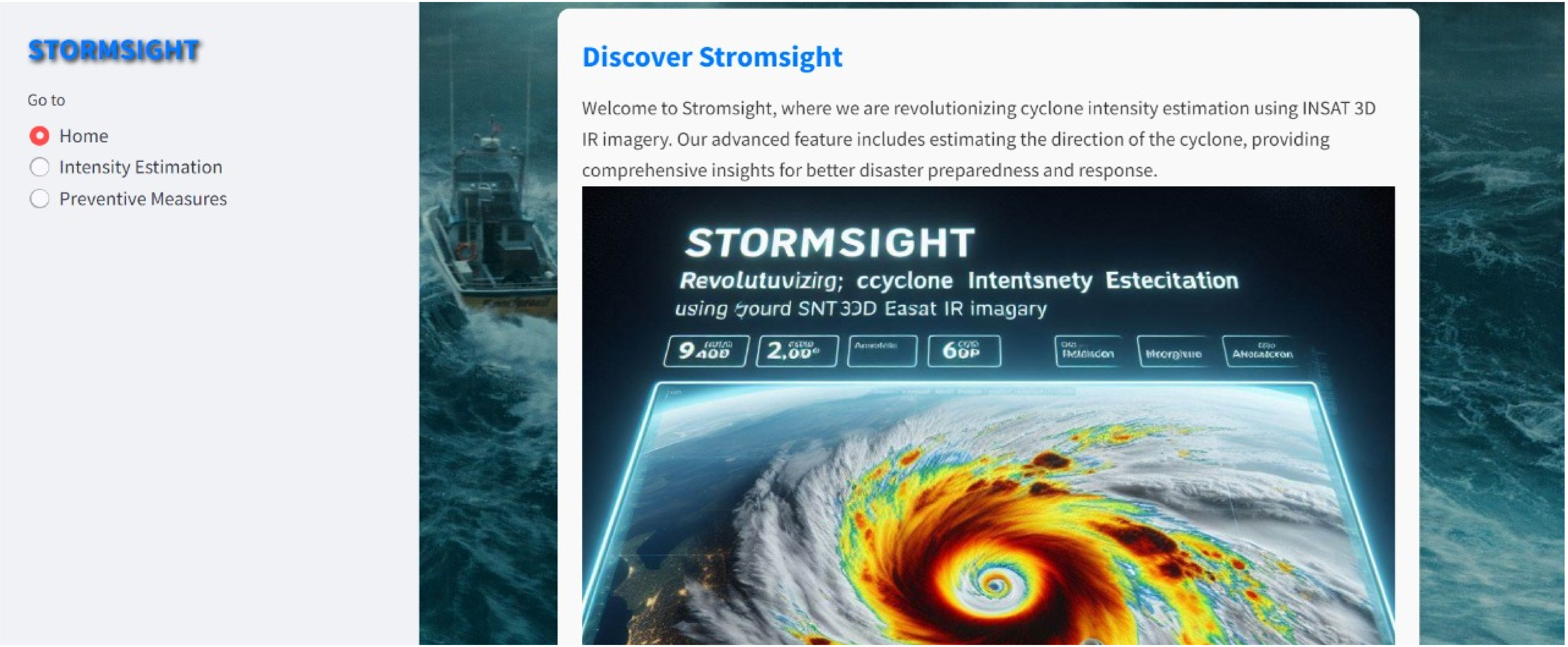
```
Function compile_model():
    model_1.compile(loss=tf.keras.losses.mse,
                    optimizer=tf.keras.optimizers.Adam(lr=0.002),
                    metrics=["mse"])
    early_stopping = tf.keras.callbacks.EarlyStopping(monitor="loss", patience=10, mode='min')

Compile Model Function End

Function fitting_model():
    history_1 = model_1.fit(train_data, epochs=50, callbacks=[early_stopping])

Fitting Model Function End
```

Pseudo code

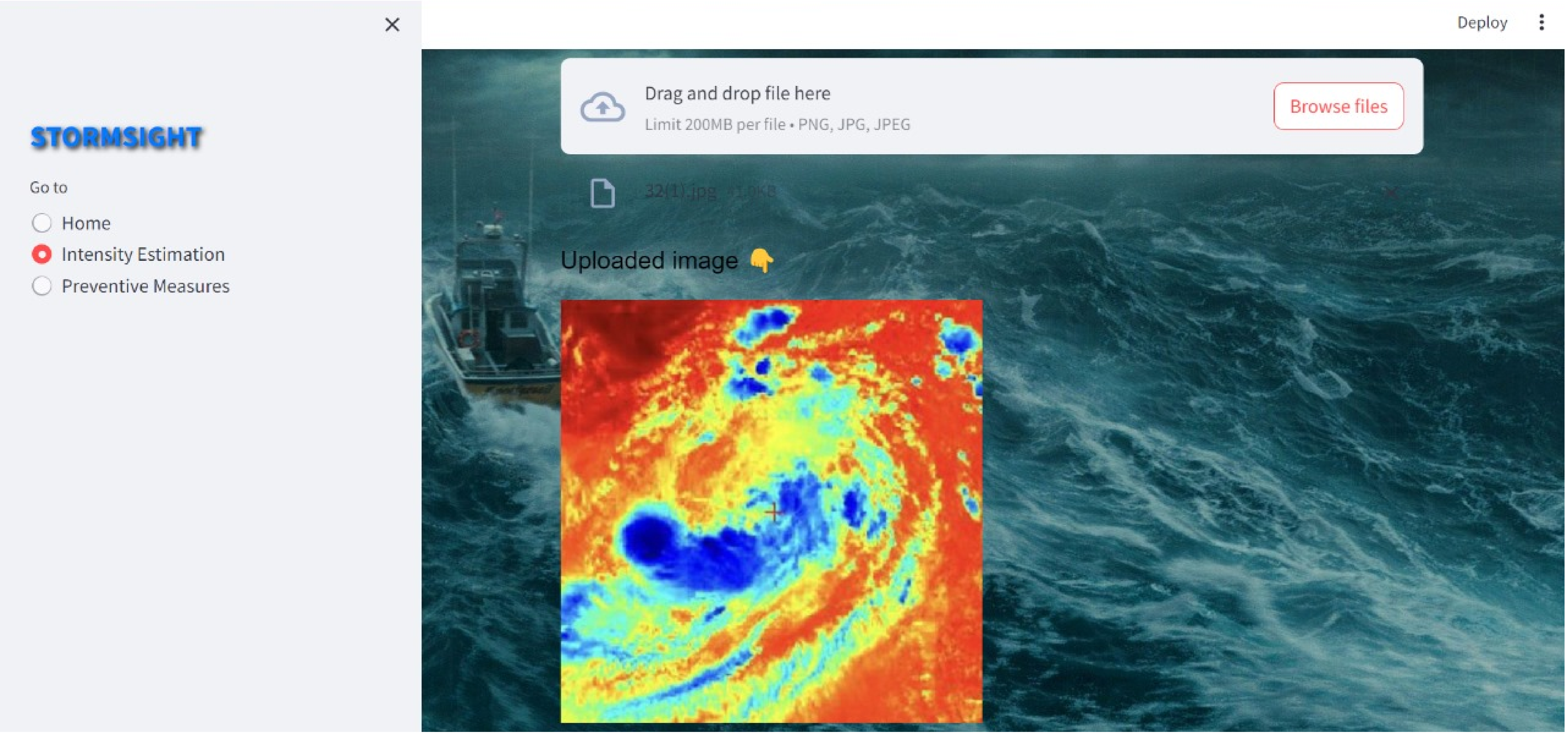
```
Function load_and_prep_image(filename, img_shape=256):
    img = tf.io.read_file(filename)
    img = tf.image.decode_image(img, channels=3)
    img = tf.image.resize(img, size=[img_shape, img_shape])
    img = img / 255.
    return img

Load And Prep Image Function End


Function pred_and_plot(model, filename):
    img = load_and_prep_image(filename)
    pred = model.predict(tf.expand_dims(img, axis=0))
    plt.imshow(img)
    plt.title(f"Prediction: {pred}")
    plt.axis(False)

Pred ANd Plot Function End
```

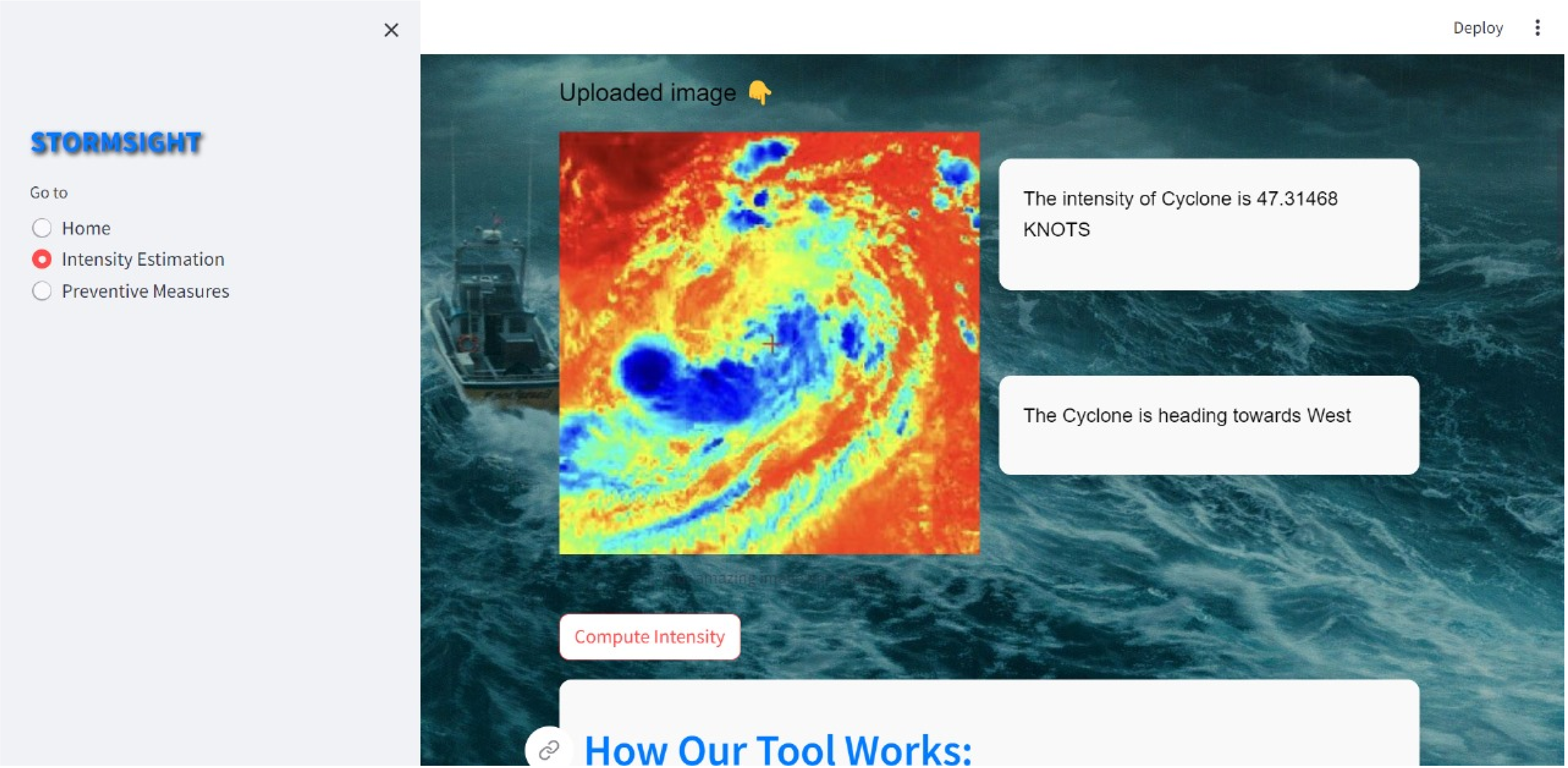
IMPLEMENTATION SCREENSHOTS

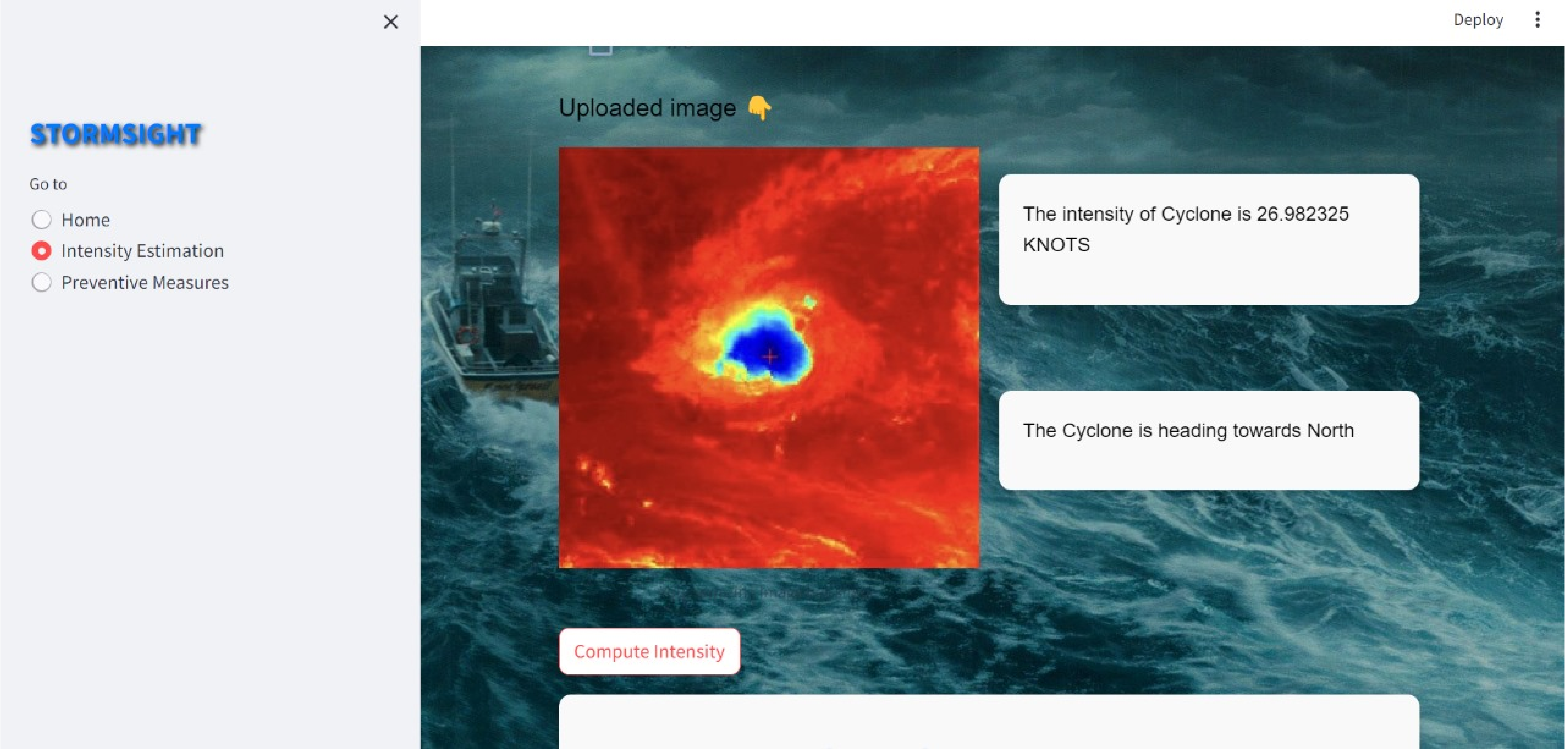
Home Page:



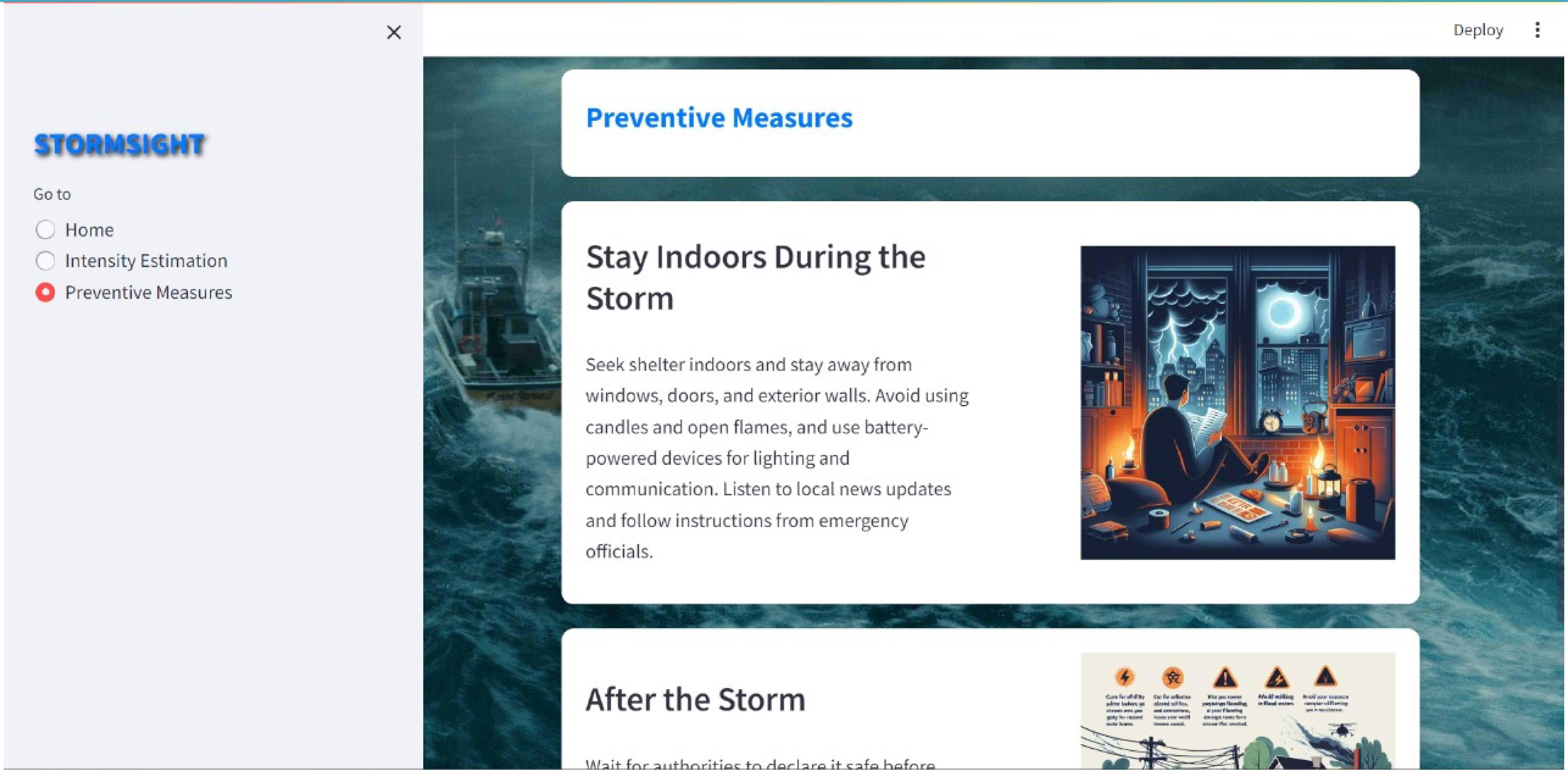
Intensity Estimation Page: 1

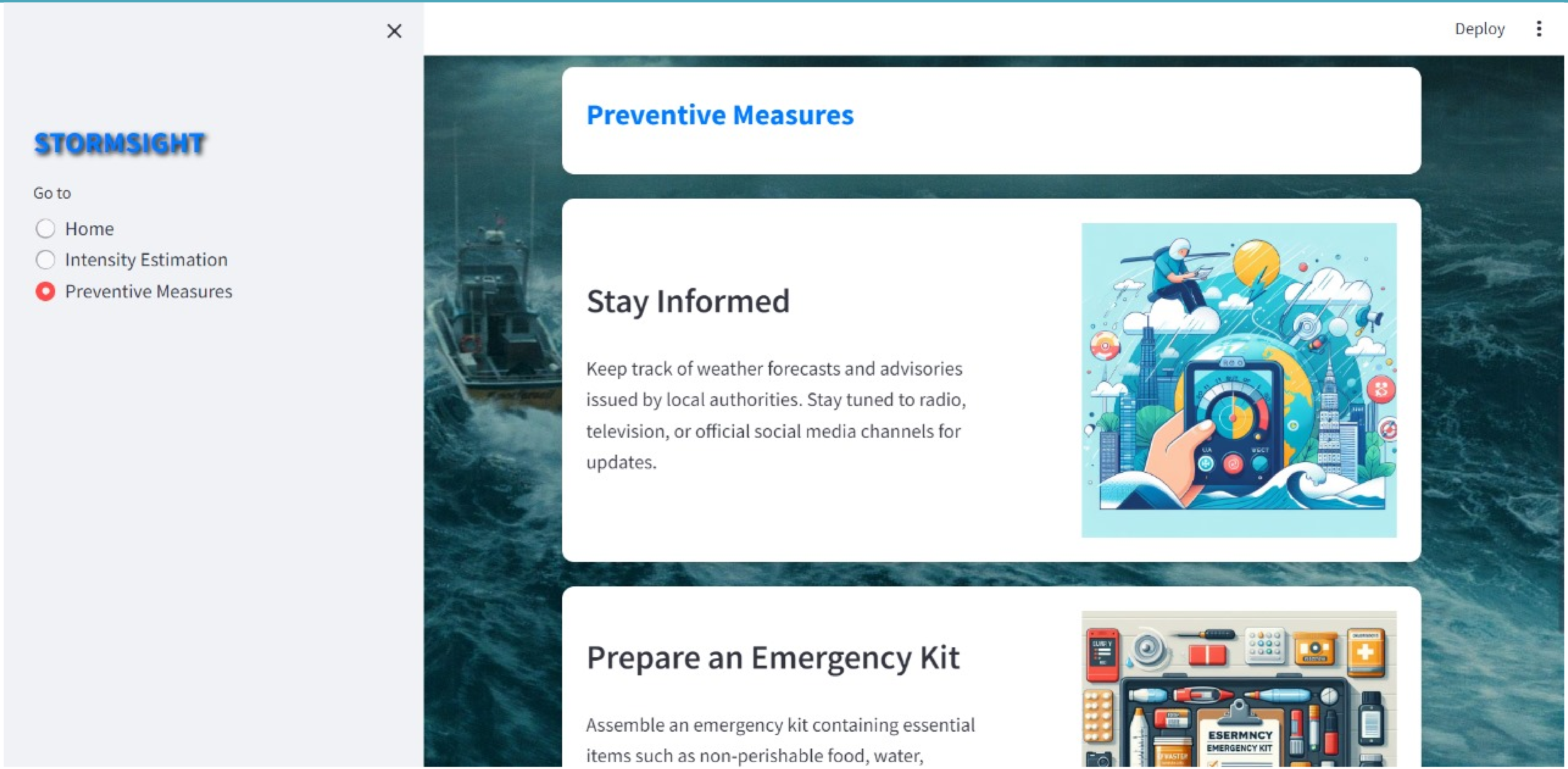

Deploy
STORMSIGHT
Go to
Home
Intensity Estimation
Preventive Measures
Drag and drop file here
Limit 200MB per file • PNG, JPG, JPEG
Browse files
Uploaded image 👇


Deploy
STORMSIGHT
Go to
Home
Intensity Estimation
Preventive Measures
Uploaded image
The intensity of Cyclone is 47.31468 KNOTS
The Cyclone is heading towards West
Compute Intensity
How Our Tool Works:


Deploy
STORMSIGHT
Go to
Home
Intensity Estimation
Preventive Measures
Uploaded image
The intensity of Cyclone is 26.982325 KNOTS
The Cyclone is heading towards North
Compute Intensity

Preventive Measures:




Deploy
STORMSIGHT
Go to
Home
Intensity Estimation
Preventive Measures
Preventive Measures
Stay Informed
Keep track of weather forecasts and advisories issued by local authorities. Stay tuned to radio, television, or official social media channels for updates.
Prepare an Emergency Kit
Assemble an emergency kit containing essential items such as non-perishable food, water,
ESERMNCY
EMERGENCY KIT

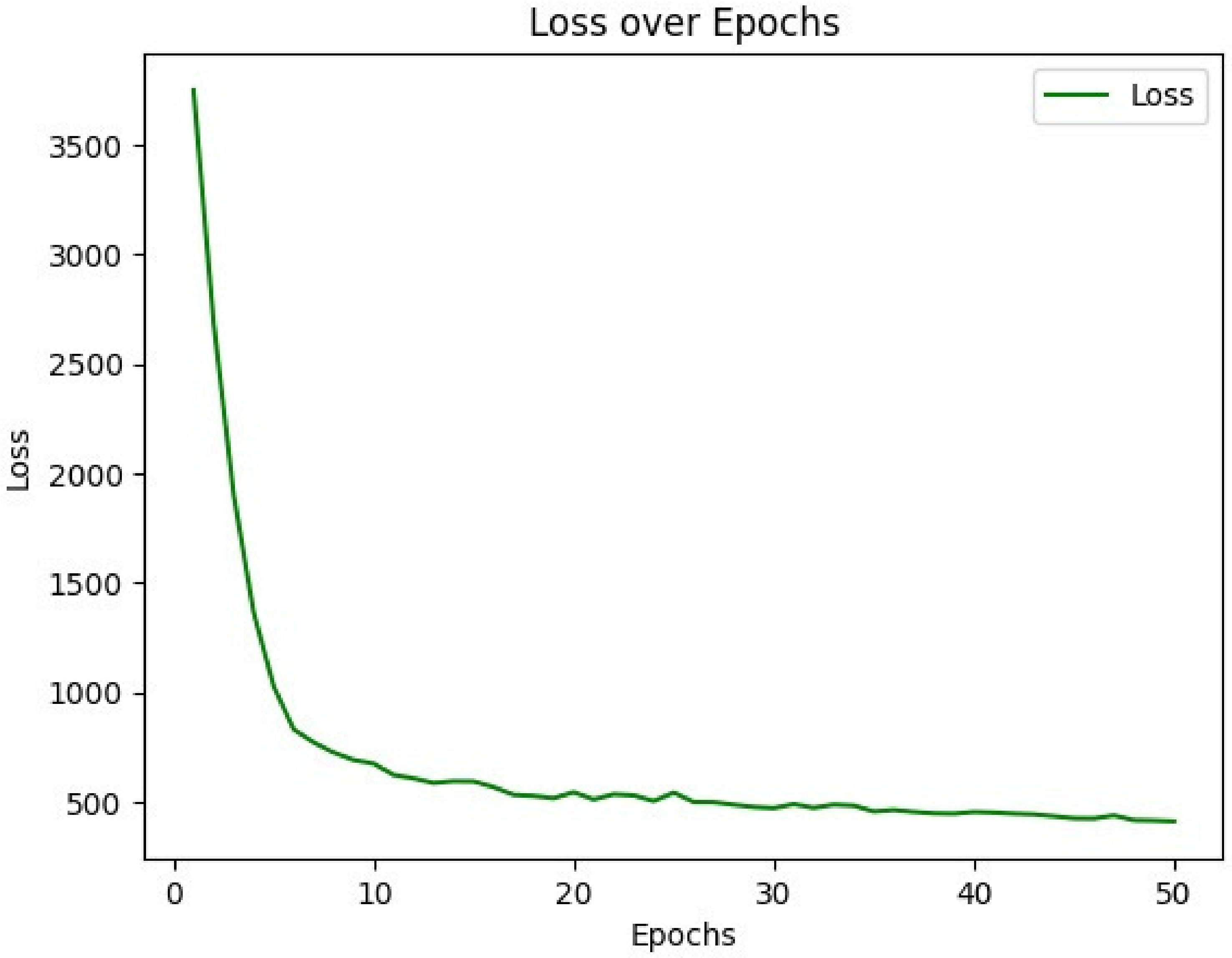
Accuracy Metrics and Evaluation methods

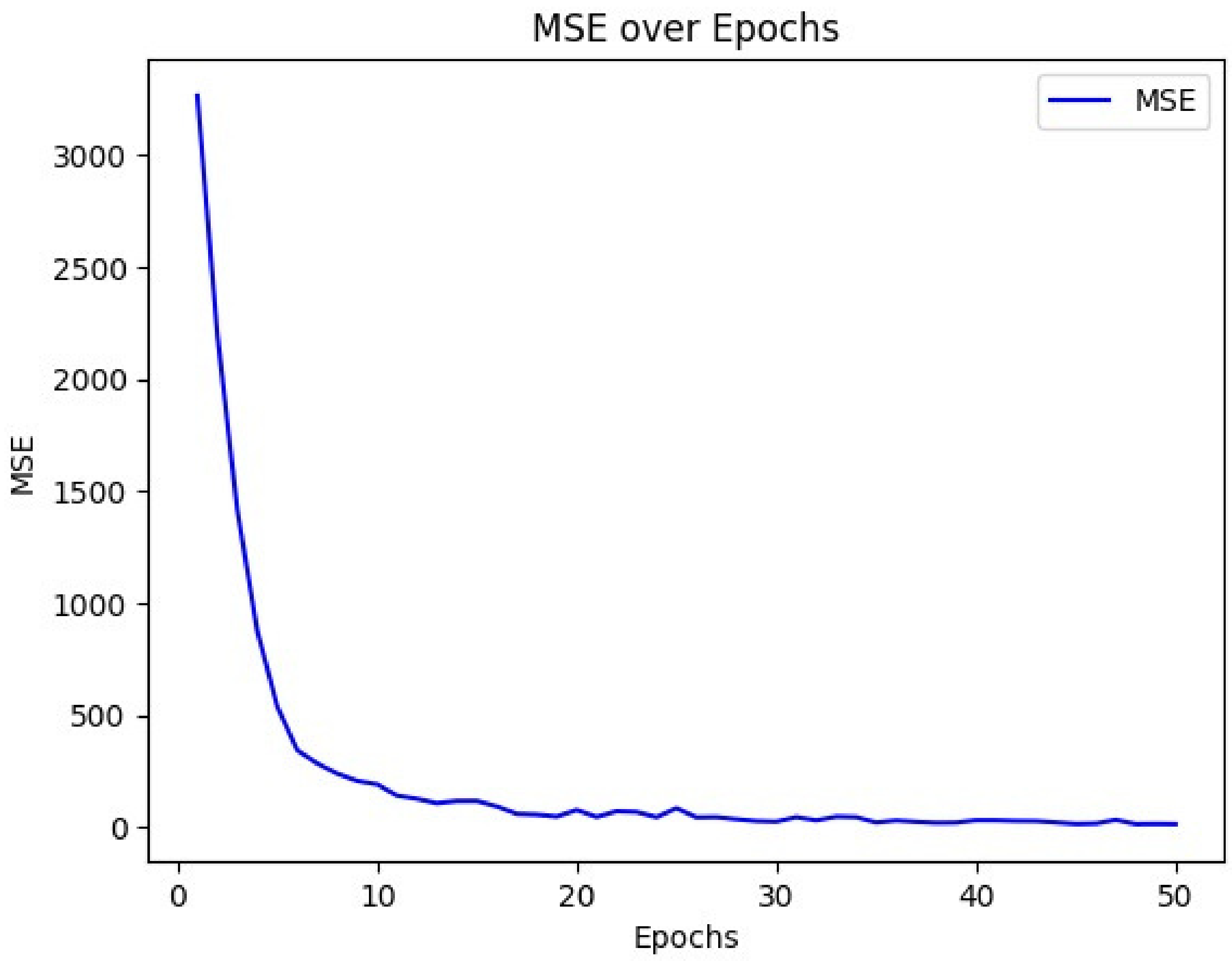
Mean Square Error value of 12.4838

RMSE: Approximately 3.53 (rounded to two decimal places)

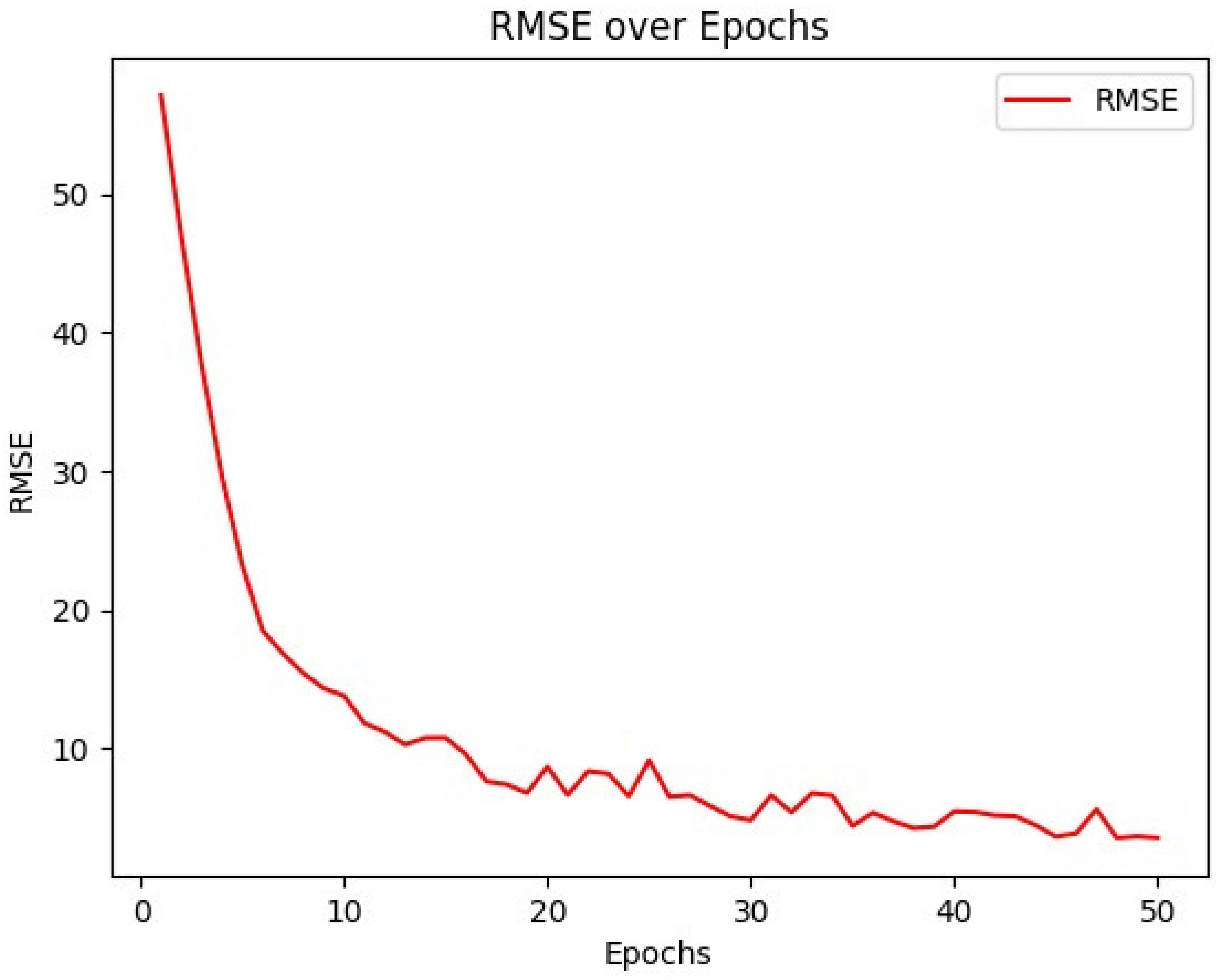
Loss : 410.2502

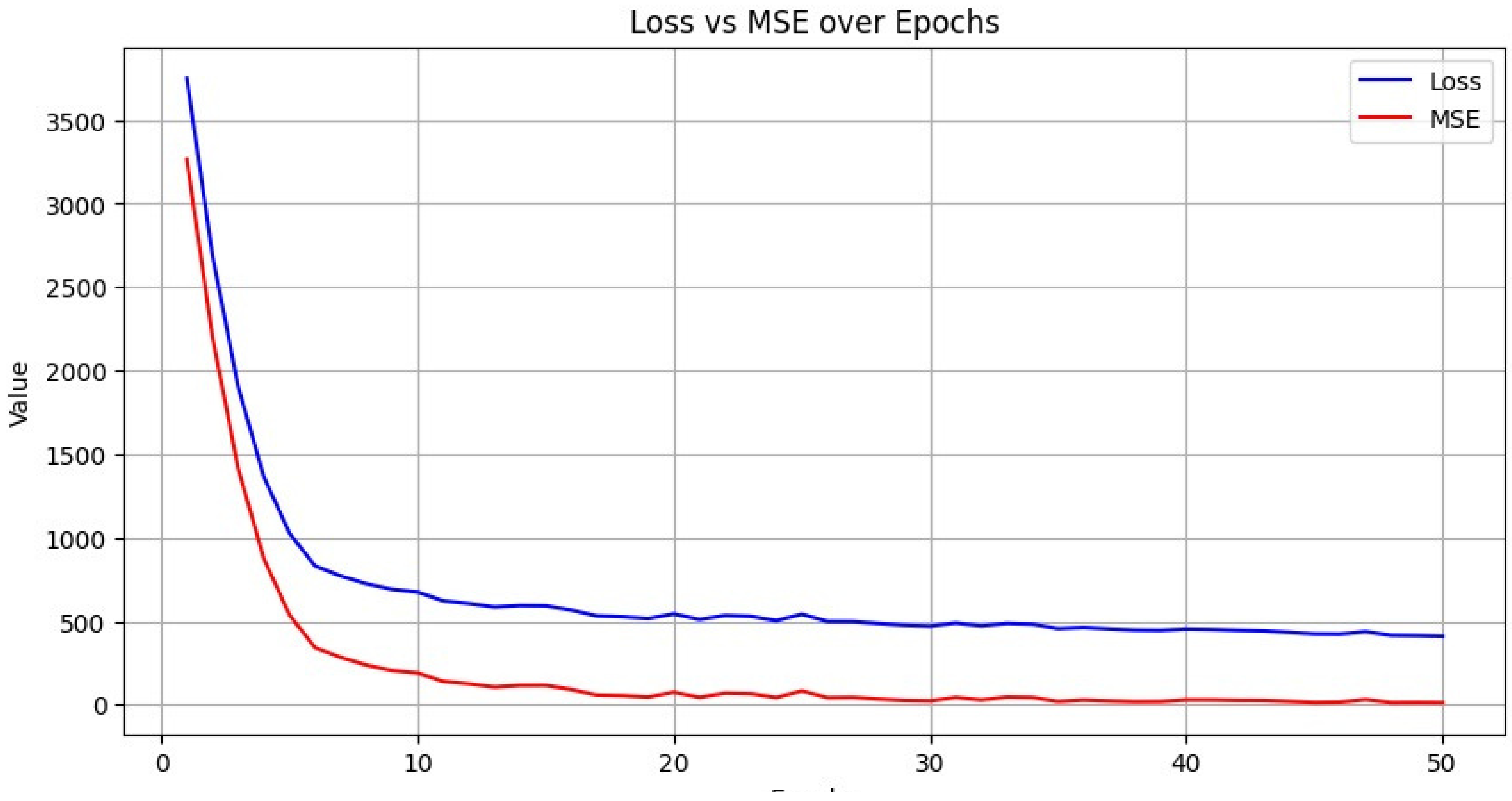
RESULT ANALYNIS AND GRAPHS





RESULT ANALYNIS AND GRAPHS





Conclusion:

The Cyclone Intensity Estimation module achieved impressive performance with a RMSE of 3.53. This signifies that the model's predictions closely matched the actual labels, indicating robust learning and prediction capabilities. The low RMSE value suggests that the model effectively minimized errors during the training process.

MSE value of 12.4838 indicates relatively low error on average
RMSE: Approximately 3.53 (rounded to two decimal places)
Loss : 410.2502

The Intensity Estimation model achieved an MSE of 3.53 on the test set.

FUTURE SCOPE

- Implementation of strormsight using video clips as input could enhance cyclone direction estimation by providing higher temporal resolution and dynamic behavior analysis for more accurate forecasting.
- Another potential future scope of the project is to enhance its capability to determine the specific location where the cyclone will make landfall.
- Expanding the project's scope to consider population density in affected areas would significantly enhance its ability to understand the human impact of cyclones
- Evaluating the impact on various sectors, including factories and industries, is essential for understanding the broader socio-economic implications of cyclones.

References

1. Jinkai Tan, Qidong Yang, Junjun Hu, Qiqiao Huang and Sheng Chen, "Tropical Cyclone Intensity Estimation Using Himawari-8 Satellite Cloud Products and Deep Learning", MDPI, 2022.
2. Cyclone Intensity Estimation Using INSAT-3D IR Imagery and deep learning (Survey Paper)“2023
3. Nair Srujan, Kulkarni Kshitij, Jain Hariprasad and Viju O. John, "A Deep Learning Framework for the Detection of Tropical Cyclones from Satellite Images", IEEE Geoscience and Remote Sensing Letters, 2022.
4. Chong Wang and Gang Zheng, "Tropical Cyclone Intensity Estimation from Geostationary Satellite Imagery Using Deep Convolutional Neural Networks", IEEE Transactions on Geoscience and Remote Sensing, vol. 60, 2021.
5. Manil Maskey, Rahul Ramachandran, Muthukumaran Ramasubramanian, Iksha Gurung, Brian Freitag, Aaron Kaulfus, et al., "Deep Learning-based Tropical Cyclone Intensity estimation system", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing.2022

References

6. A novel tropical cyclone size estimation model based on a convolutional neural network using geostationary satellite imagery”2021
7. An effective tropical cyclone intensity estimation model using Convolutional Neural Networks”2021
8. Tropical Cyclone Intensity Probabilistic Forecasting System Based on Deep Learning”2023
9. J. P. Cangialosi, E. Blake, M. DeMaria et al., “Recent progress in tropical cyclone intensity forecasting at the national hurricane center,” Weather and Forecasting, vol. 35, no. 5, pp. 1913–1922, 2020.
10. Amit Kumar, Anil Kumar Singh, J. N. Tripathi, M. Sateesh and Virendra Singh, "Evaluation of INSAT-3D-derived Hydro-Estimator and INSAT Multi-Spectral Rain Algorithm over Tropical Cyclones", 2016 Online International Conference on Green Engineering and Technologies (IC-GET).

Work Distribution

- **Durga Prasad :**

Working on the Intensity Model and checking the compatibility of the model with existing models.

- **Manideepak :**

Working on the User Interface and exploring the features that need to be considered for the direction estimation model.

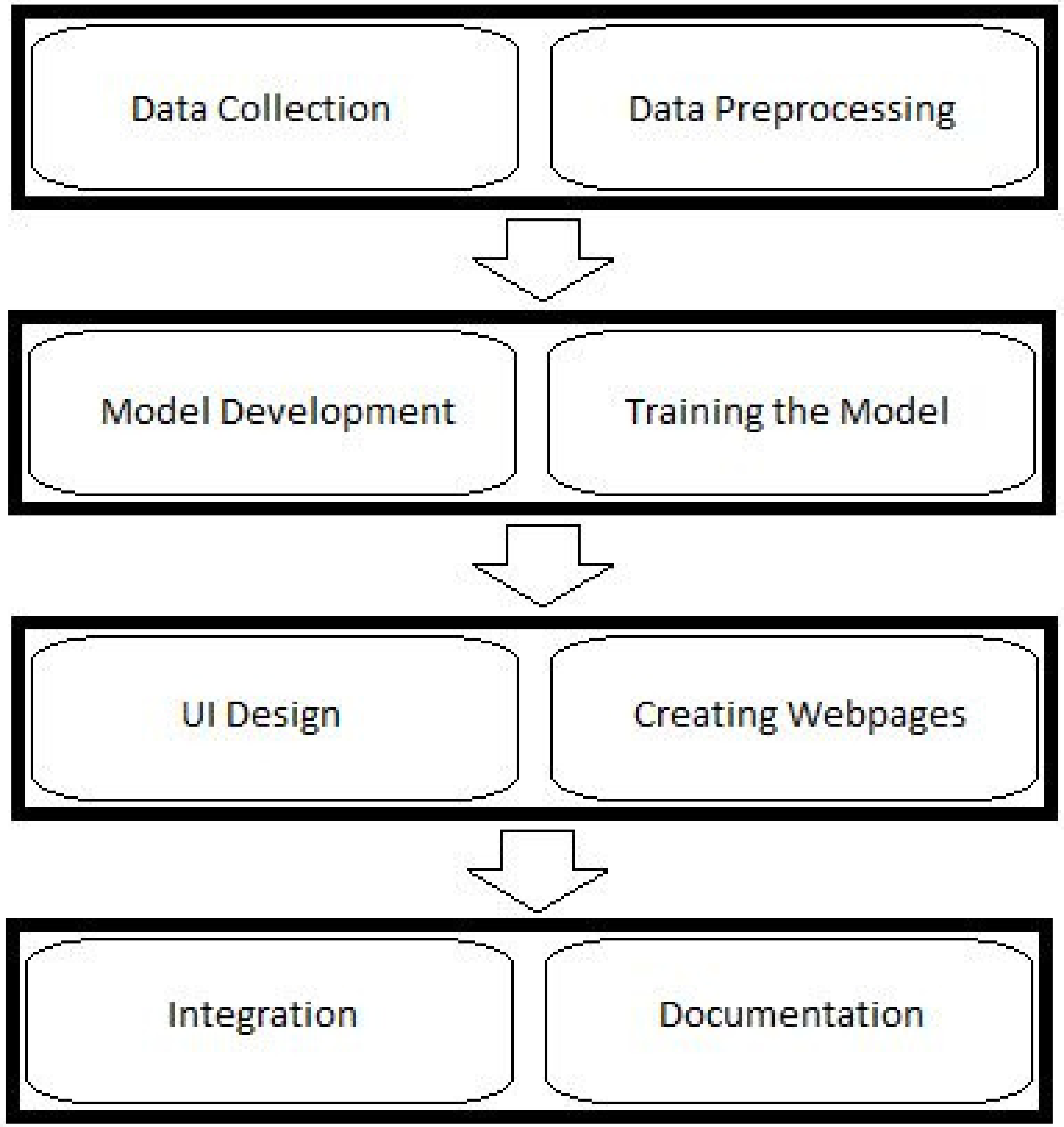
- **Shiva Kumar :**

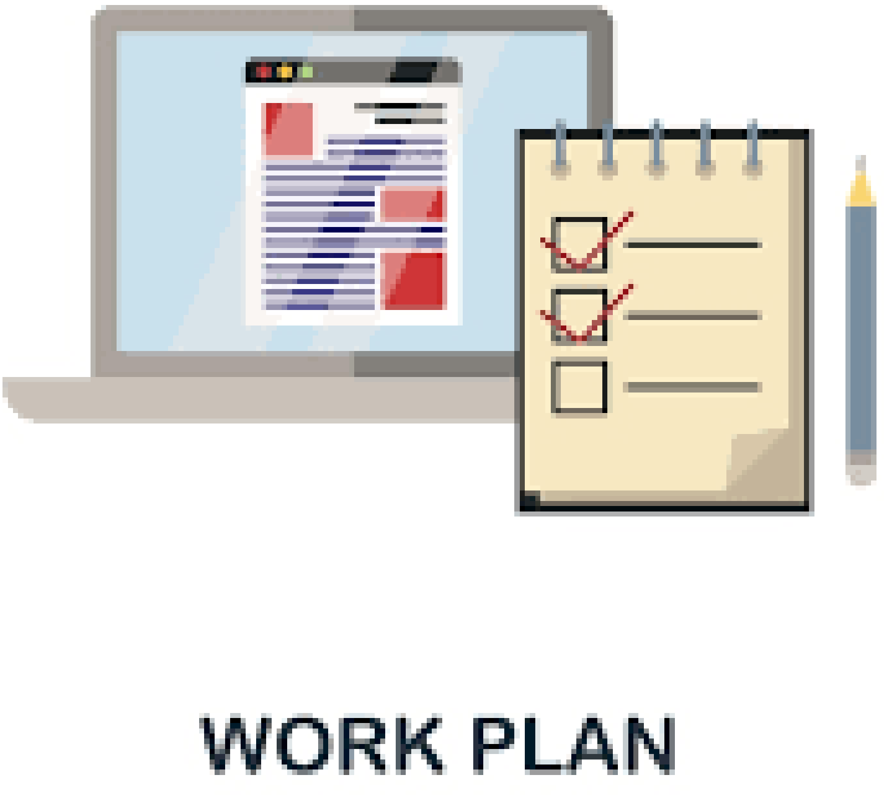
Working on the Intensity Model and checking the compatibility of the model with existing models.

- **Vijitha :**

Working on the User Interface and exploring the features that need to be considered for the direction estimation model.

Work plan


Data Collection
Data Preprocessing
Model Development
Training the Model
UI Design
Creating Webpages
Integration
Documentation


WORK PLAN

Thank You